Approach for Developing Lead Dust Hazard Standards for Residences

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Table of Contents

Table of Contents ii

List of Tables iv

List of Figures v

Acronyms vi

1. Background 1

1.1 Scope of the Analysis 1

2. Target Blood Lead Concentration 3

2.1 Selection of Endpoint 3

2.2 Selection of Target Blood Lead Levels 4

3. Estimates of Blood Lead Impacts Based on Empirical Data 4

Recent data collection by the National Health and Nutrition Examination Survey (NHANES) has made it possible to examine relationships between environmental lead exposures and blood lead concentrations in children that have not been accessible using previous collections. The methods for utilizing the NHANES empirical data to develop a residential hazard standard are described below. 4

3.1.1 Results of NHANES Analysis (Dixon, et al 2009; Gaitens et al 2009) 5

3.2 Reanalysis of the 1999-2004 NHANES Data 10

3.2.1 Model Development from Prediction of Children's Blood Lead from Residential Floor and Window-sill Dust Lead Loading 10

3.2.2 Imputation of missing dust loading values 12

3.2.3 Conversion of Dust Loading to Dust Concentration 15

3.3 Regression Models for Children's Blood Lead 17

4. Estimates of Blood Impacts Based on Biokinetic Models 22

4.1 Definition of Exposure Scenarios 22

4.1.1 Identification of Microenvironments for Dust/Soil Exposure 22

4.1.2 Time Spent in Microenvironments 23

4.1.3 Soil and Dust Exposure Metrics 25

4.1.4 Relative Contributions of Floor and Window-sill Dust to Lead Exposures 27

4.1.5 Background (Non-dust) Lead Exposures and Exposure Factors 27

4.2 Analysis of Lead Dust Hazard Standards 28

4.3 Biokinetic Models 29
4.3.1 Biokinetic Model Inputs 30
4.3.2 Predicted Blood-lead Levels from Biokinetic Models 30
5. Predicted Blood Lead Levels 32
5.1 Predicted Blood-lead Levels Associated with Candidate Dust-Loading Hazard Standards 32
5.2 Predicted Proportions of Children above Target Blood-lead Levels 36
6. Sensitivity Analysis of Model Predictions to Variations in Key Inputs 40
6.1 Models Based on Empirical Data 40
6.2 Biokinetic Models 42
7. Summary 45
7.1 Approaches for Estimating Blood-lead Concentrations Associated with Candidate Hazard Standards 45
7.2 Proportions of Children Predicted to Have Blood-lead Concentrations above Target Levels 45
7.3 Major Sources of Uncertainty in Blood-lead Estimates 45
8. References 47

List of Tables

Table 3-1. Descriptive Statistics for Demographic and Lead Variables (Dixon et al. 2009) 5

Table 3-2. Linear Model Results for Log Children's PbB[a] (Dixon et al. 2009) 8

Table 3-3. Regression Model Used to Impute Window-sill Dust Loading for Records with Missing Values[a] 14

Table 3-4. Floor Dust Blood-lead Regression Results (Dust Concentration Based on Empirical and Mechanistic Models) 18

Table 4-1. Estimates of Children's Time (Hours) Spent in Microenvironments (CHAD) 25

Table 4-2. Estimated Soil, Floor, and Sill Dust Lead Concentrations in Microenvironments, Baseline Scenario 27

Table 4-3. Baseline Input Values for the Biokinetic Model 28

Table 5-1. Predicted Blood-lead Concentrations at "Baseline" and NHANES Geometric Mean Values for 1- to 5-Year Olds 33

A. Predicted Concentrations at "Baseline" 33

Table 5-2. Predicted Geometric Mean Blood-lead Concentrations Associated with Candidate Residential Dust Lead Hazard Standards, Based on the Dixon et al. (2009) Regression Model.................................. 34

Table 5-3. Predicted Geometric Mean Blood-lead Concentrations Associated with Candidate Residential Dust Lead Hazard Standards, Based on the NHANES Quasi-likelihood Regression Model 35

Table 5-4. Predicted Geometric Mean Blood-lead Concentrations Associated with Candidate Residential Dust Lead Hazard Standards, Based on the IEUBK and Leggett Biokinetic Models.................................. 36

Table 6-1. Influence of Dust Loading, Dust Concentration, and Other Covariates in the Dixon et al. (2009) and NHANES Quasi-Likelihood Regression Models for Children's Blood Lead 41

Table 6-2. Baseline Lead Intake and Uptake Model[a] and Sensitivity to Changes in Intake Values 43

List of Figures

Figure 1-1. Methodology for evaluating blood lead impacts of dust lead hazard standards. 2

Figure 3-1. Predicted blood lead at median floor and windowsill dust loading as a function of age (years), Dixon et al. (2009) model. 7

Figure 3-2. Predicted GM blood lead concentrations versus floor dust loading by scenario. (See text for scenario definitions). 9

Figure 3-3. Comparison of predicted versus measured ln(windowsill dust lead loading). 12

Figure 3-4. Smootheda relationship between floor dust- and blood-lead concentrations, 1999–2004 NHANES data, floor dust loading <10 μg/ft^2. 15

Figure 3-5. Mechanistic model for indoor dust generation, transport, and removal (Source: U.S. EPA, Figure A-2). 16

Figure 3-6. Comparison of dust lead concentrations predicted by the empirical and mechanistic models. 17

Figure 3-7. Predicted blood-lead concentrations versus age based on the quasi-likelihood model, central tendency scenario. 19

Figure 3-8. Comparison of predicted and measured blood-lead concentrations versus measured values, quasi-likelihood GLM based on floor dust loadings. 21

Figure 4-1. Age patterns of blood-lead predictions by the IEUBK and Leggett models (median floor and windowsill dust loading). 30

Figure 4-2. Blood-lead concentrations predicted by the IEUBK and Leggett models as a function of floor dust lead loading (median windowsill dust loading)....................................31

Figure 5-1. Predicted blood lead concentrations as a function of floor dust lead loading.........................32

Figure 5-2. Predicted proportions of children with blood-lead concentrations greater than 5 μg/dL (floor dust lead loading 5 μg/ft^2, blood-lead GSD = 2.1). 38

Figure 5-3. Predicted proportions of children with blood-lead concentrations greater than 2.5 μg/dL (floor dust lead loading 5 μg/ft^2, blood-lead GSD = 2.1). 38

Figure 5-4. Predicted proportions of children with blood-lead concentrations > 5 μg/dL (floor dust loading 5 μg/ft^2).. 39

Figure 5-5. Predicted proportions of children with blood-lead concentrations > 2.5 μg/dL (floor dust loading 5 μg/ft^2).. 39

Acronyms

CDC	Centers for Disease Control and Prevention
CFR	Code of Federal Regulations
COF	child-occupied facility
CHAD	Consolidated Human Activity Database
CT	central tendency
GLM	generalized linear model
GM	geometric mean
GSD	geometric standard deviation
GSE	geometric standard error
HUD	Housing and Urban Development, Department of
IEUBK	Integrated Exposure Uptake Biokinetic Model
LOD	level of detection
LRRP	Lead Renovation, Repair, and Painting Rule
NAAQS	National Ambient Air Quality Standard
NSLAH	National Survey of Lead and Allergens in Housing
NHANES	National Health and Nutrition Examination Survey
PIR	poverty-to-income ratio
QL	quasi-likelihood
SAB	Science Advisory Board
TSCA	Toxic Substances Control Act
TRW	Technical Review Workgroup for Lead
EPA	U.S. Environmental Protection Agency

1. Background

Section 403 of the Toxic Substances Control Act (TSCA) of 1976 directs the U.S. Environmental Protection Agency (EPA) to promulgate regulations that identify, for the purposes of Title X and Title IV of TSCA, dangerous levels of lead in paint, dust, and soil. EPA promulgated regulations pursuant to TSCA section 403 on January 5, 2001 and codified them at 40 Code of Federal Regulations (CFR) part 745, subpart D (USEPA 2001). These hazard standards identify dangerous levels of lead in paint, dust, and soil and provide benchmarks on which to base remedial actions that would safeguard children and the public from the dangers of lead. Lead-based paint hazards in target housing and child-occupied facilities are defined in these standards as paint-lead, dust-lead, and soil-lead hazards. A paint-lead hazard is defined as any damaged or deteriorated lead-based paint, any chewable lead-based painted surface with evidence of tooth marks, or any lead-based paint on a friction surface if lead dust levels underneath the friction surface exceed the dust-lead hazard standards. A dust-lead hazard is surface dust that contains a mass-per-area concentration of lead equal to or exceeding 40 micrograms per square foot ($\mu g/ft^2$) on floors or 250 $\mu g/ft^2$ on interior window sills based on wipe samples. A soil-lead hazard is bare soil that contains total lead equal to or exceeding 400 parts per million (ppm) in a play area or an average of 1,200 ppm of bare soil in the rest of the yard based on soil samples.

On August 10, 2009, EPA received a petition from several environmental and public health advocacy groups requesting that EPA amend regulations issued under Title IV of TSCA (Sierra Club et al. 2009). Specifically, the petitioners requested that EPA lower the Agency's dust-lead hazard standards issued pursuant to section 403 of TSCA from 40 $\mu g/ft^2$ to 10 $\mu g/ft^2$ or less for floors and from 250 $\mu g/ft^2$ to 100 $\mu g/ft^2$ or less for window sills. On October 22, 2009, EPA granted this petition under section 553(e) of the Administrative Procedures Act, 5 U.S.C. 553(e) (USEPA 2009). In granting this petition, EPA agreed to commence the appropriate proceeding, but did not commit to a particular schedule or to a particular outcome.

In June 2010, EPA issued a Proposed Approach for Developing Lead Dust Hazard Standards for Residences (USEPA 2010a) and submitted the document to the Science Advisory Board (SAB) Lead Review Panel for a consultation. The document discussed methods for evaluating the health hazards associated with exposure to lead-contaminated residential floor and window-sill dust, including approaches for estimating dust-lead loading and lead concentrations in residences, evaluation of exposure patterns, estimation of lead intake from dust and other sources, identification of sensitive populations, and prediction of blood-lead impacts of dust-lead exposure. The SAB Panel met July 6–7, 2010 and provided comments on the Proposed Approach to EPA on August 20 (SAB 2010). This report takes those comments into consideration in developing several candidate standards for residences.

1.1 Scope of the Analysis

This document describes the approach for developing dust-lead hazard standards for floors and window sills in residences. As recommended by the SAB (SAB, 2010), candidate dust-lead hazard standards are estimated using two different methods. The first involves the use of empirical models, and the second involves the use of biokinetic models. A range of candidate standards for lead-dust loading on floors and window sills is evaluated with regard to their impacts on children's blood lead concentration with the empirical and biokinetic models, and comparisons are made of the proportions of children with blood-lead concentrations above specified target concentrations predicted by the various models. Figure 1-1 provides an overview of the empirical and biokinetic approaches for developing candidate hazard standards for residences.

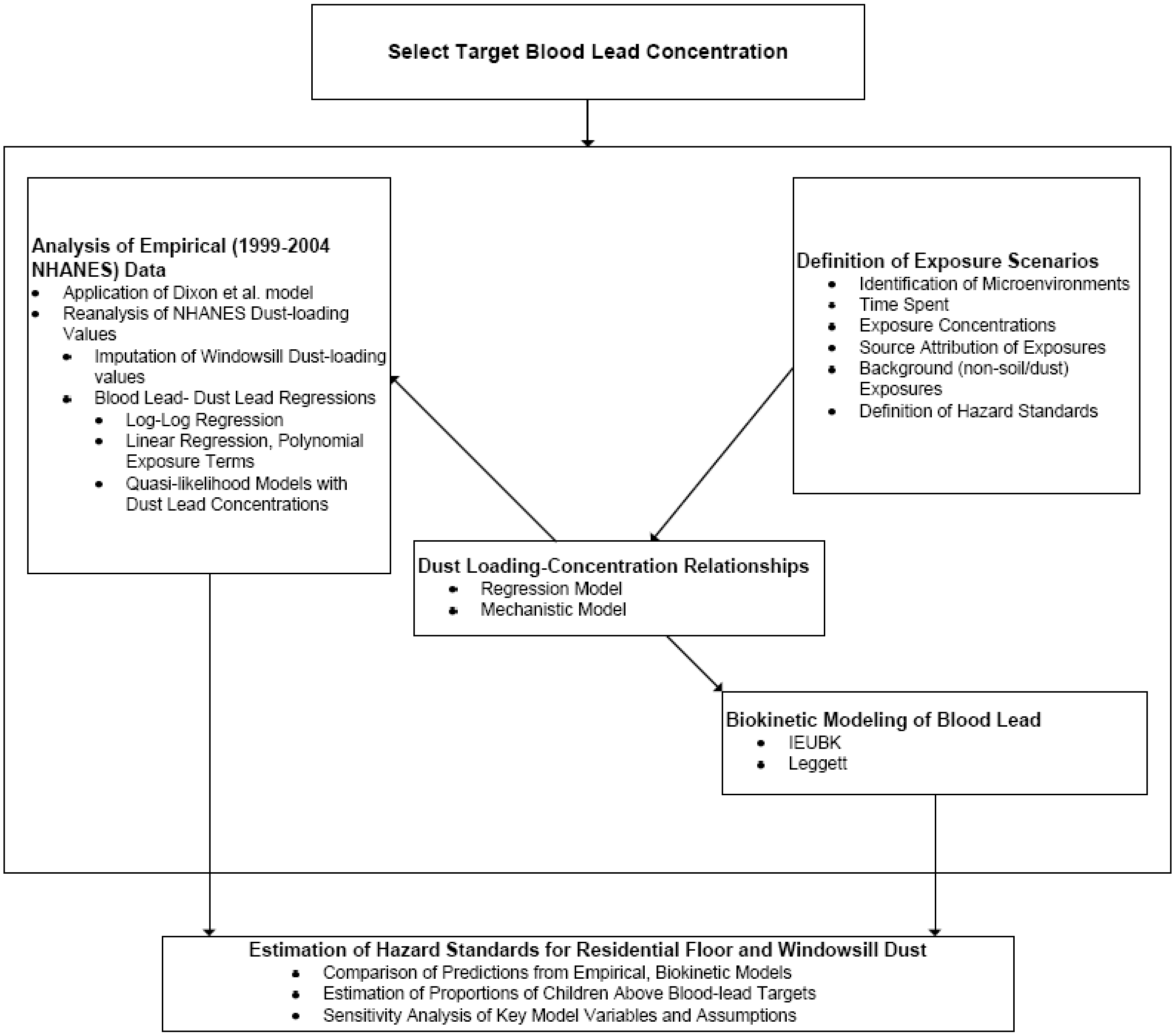

Figure 1-1. Methodology for estimating residential dust lead hazard standards.

The first step for both the empirical and biokinetic approaches, ***Select Target Blood Lead Concentration***, involves the selection of target blood lead levels. The proposed approach for residential hazard standards will focus on target blood lead levels that are associated with IQ effects in children; three target blood lead levels have been selected which are at the low end of the dose-response curve. The remaining steps of both approaches are then applied to examine the impact of various candidate dust-lead levels (hazard standards) for floors and window sills on the proportions of children with blood-lead concentrations above the specified target concentrations.

The empirical approach (left-hand side of Figure 1-1) involves the estimation of blood-lead impacts based on analyses of empirical data from the 1999–2004 National Health and Nutrition Examination Survey (NHANES), as originally analyzed by coinvestigators Gaitens et al. (2009) and Dixon et al. (2009). Two analyses were used in the empirical approach. First, the regression relationships among floor and window-sill dust, other covariates, and blood-lead concentrations that Dixon et al. (2009) derived were applied to predict blood-lead levels for the various hazard standards (combinations of floor and window-sill dust loadings). The second was an independent reanalysis of the NHANES data to derive alternate models for predicting blood-lead impacts; the variations from the Dixon et al. (2009) approach included changes to the form of the dust-loading variables and application of models that are inherently linear at low lead exposures, a relationship that is supported by a wide range of biokinetic data, and regression of blood-lead values against estimated dust concentrations, rather than dust loading.

The remaining steps for the biokinetic approach are shown on the right-hand side of Figure 1-1. First, exposure scenarios for children are defined which involves identifying microenvironments in which to evaluate exposures, estimating time spent in the microenvironments, developing exposure metrics for environmental media in the various microenvironments (air, soil, and dust), estimating the relative contributions of the different media (proportion of lead intake from soil, window-sill versus floor dust) to the exposure, estimating background or non-dust lead exposures (diet and drinking water), and defining the candidate hazard standards (numerical floor and window sill loading values) to be evaluated. Exposure scenarios include both residential and non-residential (child-occupied facilities and public and commercial buildings) microenvironments, to provide accurate characterization of total lead exposure.

Use of the biokinetic models requires quantitative estimates of dust and soil concentration from which lead intake can be estimated. Thus, it is necessary to convert the lead loadings for the exposure scenarios into lead concentrations in floor and window-sill dust. However, very little empirical data are available that can be used to directly assess the relationship between residential dust loading and concentration. Two approaches (regression and mechanistic modeling) are used to derive estimates of dust-lead concentration from dust loading.

Two biokinetic models were used to estimate blood lead concentrations including EPA's Integrated Exposure Uptake Biokinetic Model for Lead in Children (IEUBK) (USEPA 2010c), and the Leggett model (Leggett 1992). Information from the exposure scenarios is used to estimate relative contributions of exposures from different sources (soil, dust, air, diet, and water) and in different microenvironments.

Finally, blood-lead predictions (estimated geometric means and proportions above the various blood-lead targets) derived with the empirical and biokinetic models are then compared for the candidate floor and window-sill hazard standards (see bottom of Figure 1-1).

Monte Carlo methodology was not used to evaluate the impacts of variability and uncertainty in model parameters on blood-lead estimates as insufficient data exist concerning the potential variability in many key model variables to support informative Monte Carlo modeling. Instead, point estimates of central tendency (geometric mean) blood-lead concentrations in children are derived utilizing statistical models based on empirical data and on biokinetic models of blood lead, coupled with assumptions regarding distributions of highly uncertain variables. The sensitivity of the deterministic relationships between dust lead and blood lead to changes in key variables and covariates is explored through sensitivity analyses. As presented in Section 6, the modeling inputs and assumptions that most strongly affect the predicted blood-lead distributions associated with candidate lead-dust hazard standards have been identified, based on the measures of statistical uncertainty from the empirical analyses and sensitivity analyses of the biokinetic models.

2. Target Blood Lead Concentration

2.1 Selection of Endpoint

There is a strong consensus within the public health community that the adverse effects of lead exposure are greatest in children and that impairment of neurological development is the "critical effect" (the effect occurring at the lowest exposure levels) (USEPA 2006, CDC 2005, 2009a, Bellinger 2008, Lanphear et al. 2005). The intelligence quotient (IQ) is the most commonly measured neurodevelopmental endpoint in lead-exposed children, and blood lead is the most common exposure/dose metric in epidemiological studies. A number of recent studies (Canfield et al. 2003, Chiodo et al. 2004, Jusko et al. 2008, Lanphear et al. 2005, Miranda et al. 2007, Surkan et al. 2007, Téllez-Rojo et al. 2006) have reported decrements in IQ and other adverse effects at blood lead levels less than 10 µg/dL. It is generally agreed that no specific "threshold" blood lead level for adverse effects on IQ in children has been identified. In addition to IQ measures, there is rapidly accumulating evidence that lead also affects other aspects of neurological development, and that in many of these studies, these effects were also observed in children at blood lead levels less than 10 µg/dL. These studies are reviewed in USEPA (2006); more recent reports include an association between early lead exposure and increased incidence of ADHD (Nigg et al. 2008, 2010), ADHD coupled with other behavior problems (Roy et al. 2008), as well as additional observations of increased criminal behavior (Wright et al. 2008) and other behavioral problems in young children (Chen et al. 2007).

Although there are some uncertainties in using both blood lead as a measure of exposure and IQ changes as an outcome measure, it is more difficult to generalize the results of the more complex neurobehavioral effects identified above. Therefore, children's IQ has been chosen as the primary critical endpoint for determining the potential blood lead levels of concern. In making this choice, it is recognized that IQ effects do not capture the entire spectrum of adverse neurological effects associated with lead exposure in children. Estimating IQ loss thus represents a lower bound on the overall adverse effects of lead exposures to children.

2.2 Selection of Target Blood Lead Levels

For purposes of this Approach, a distribution for a hypothetical child will be modeled around individual candidate hazard standards. Blood lead levels of 1, 2.5 and 5 µg/dL have been chosen in order to evaluate a range of potential hazard standards. These levels were chosen, in part, based on recent literature which shows that increases in children's blood lead from 1 to 10 µg/dL result in a greater decrement in IQ score than increases from 10 to 20 µg/dL, or from 20 to 30 µg/dL (Lanphear et al. 2005; Canfield et al. 2003; Schwartz 1994). This finding indicates a steeper dose-response relationship at blood lead levels below 10 µg/dL. Lanphear et al. (2005) derived regression relationships between several blood lead metrics (lifetime, concurrent, peak and early childhood) and IQ test results. Several different models relating blood lead metrics to IQ, which predict a wide range of IQ changes for given blood lead levels, were used. First, they developed log-linear models relating IQ changes to all blood lead metrics they examined. In these models, the relationships between IQ change and blood lead are curved, with steeper slopes at low blood lead levels. Lanphear et al. (2005) also fit piecewise models (consisting of separate linear fits for different blood lead concentration ranges) to several of the blood lead metrics, and presented the results developed for the concurrent blood lead metric. EPA (USEPA 2008) also obtained the relevant piecewise models for lifetime average blood lead concentrations based on the same data set.

3. Estimates of Blood Lead Impacts Based on Empirical Data

Recent data collection by the National Health and Nutrition Examination Survey (NHANES) has made it possible to examine relationships between environmental lead exposures and blood lead concentrations in children that have not been accessible using previous collections. The methods for utilizing the NHANES empirical data to develop a residential hazard standard are described below.

3.1 Blood Lead and Dust Lead Loading Data Collected in NHANES (1999-2004)

From 1999-2004, the NHANES collected blood lead data from its participants in the survey, as well as dust lead loadings from floors and window sills. These data were analyzed in two studies by the same group of authors which aimed to determine how various housing and demographic characteristics influenced blood lead (PbB) in children (Gaitens et al. 2009; Dixon et al. 2009).

NHANES is an ongoing program of studies conducted by the National Center for Health Statistics (NCHS) designed to assess the health and nutritional status of adults and children in the United States. The survey examines a nationally representative sample of about 5,000 persons each year. These persons are located in counties across the country, 15 of which are visited each year. The survey is unique in that it combines interviews and physical examinations. In the 1999-2004 sampling periods, dust lead loading data were also collected from homes of the participants in the survey. This provided a unique opportunity to evaluate blood lead data normally collected in NHANES participants with environmental samples collected in their homes.

Data collected in three NHANES sampling periods (1999-2000, 2001-2002, 2003-2004) on 2155 children aged 12-60 months with measured PbB were included in the study. A single floor dust sample and a single window sill dust sample were collected from the room most occupied by the child. Data for 2,065 floor dust lead samples and 1618 window sill dust samples were available for analysis. NHANES also collects information on demographic characteristics (age, race, gender, income, poverty-to-income ratio [PIR]; country of birth); household characteristics (type of home, year of construction, paint condition inside and outside home, sill and floor surface condition); and smoking behaviors.

Analyses of NHANES, which is a complex survey, required use of sampling weights in order to construct representative estimates. Dixon et al (2009) developed a weighted log-linear regression model that accounted for stratified sampling, clustering, and sampling weights to characterize the relationship between geometric mean blood lead, dust loading, and other covariates. For variables with missing values, the regressions included intercept terms to avoid eliminating large numbers of observations. The variable selection used backward stepwise elimination with the criterion $p > 0.10$. The model regressed $\log_e$ PbB against $\log_e$ floor dust lead (PbD) and $\log_e$ sill PbD, also adjusting for the previously selected variables, using a quartic function of age (in years) and a cubic function of $\log_e$ floor PbD. For the missing sill values, the $\log_e$ sill PbD values were imputed using the unweighted regression ln(sill PbD) = $2.654 + 0.524 \times \ln(\text{floor PbD})$. In Dixon et al. (2009) and in this Approach document, references to log, $\log_{e,}$, and ln all indicate the natural logarithm.

In addition, a logistic regression model was used to predict the probability that blood lead is ≥10 µg/dL and ≥5 µg/dL. Model fit was assessed using residual analysis for linear models (ignoring the survey data assumption) and analysis of deviance for the logistic models (accounting for survey weights, but ignoring clustering).

3.1.1 Results of NHANES Analysis (Dixon, et al 2009; Gaitens et al 2009)

Floor dust lead samples for 259 (14.2%) observations were below the limit of detection (LOD) of 0.16 µg. There were 714 (36.3%) observations below the LOD of 2 µg for window-sill dust lead. For the analysis, floor and sill dust lead values below the LOD were assigned values of 0.11 µg/ft^2 and 1.41 µg/ft^2, respectively (i.e., LOD/√2, as recommended by NHANES and the NCHS). Similarly, for blood lead, the non-detects were replaced with 0.21 µg/dL. Table 3-1 provides the descriptive statistics for some of the demographic characteristics and the blood-lead and dust-lead variables.

Table 3-1. Descriptive Statistics for Demographic and Lead

Variables (Dixon et al. 2009)

Variable		N	Weighted percent[a]
Gender	Males	1,139	54.21
	Females	1,016	45.79
Race /ethnicity	Non-Hispanic white	618	57.09
	Non-Hispanic black	634	15.32
	Hispanic	837	23.82
	Other	66	3.77
Floor dust lead (PbD)	Missing	90	-
	Non-missing	2,065	0.52 (0.03)
Sill dust lead (PbD)	Missing	537	-
	Non-missing	1,618	7.64 (1.07)
Blood lead (PbB)	(All)	2,155	2.03 (1.03)

[a] For lead-loading measurements, values = weighted geometric mean (weighted geometric standard error).

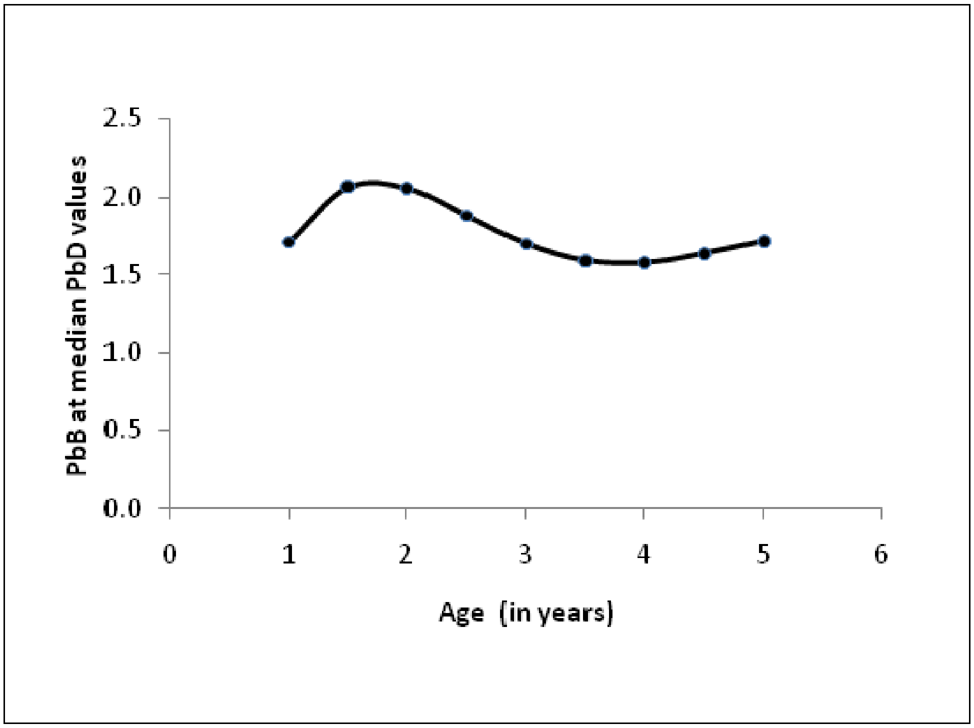

Figure 3-1. Predicted blood lead at median floor and window-sill dust loading as a function of age (years), calculated from Dixon et al. (2009) model

Figure 3-1 presents the relationship between predicted geometric mean blood lead and age using the Dixon et al. (2009) model. For constant dust concentrations, blood lead peaks between 1.5 and 3 years and then slowly declines with age. These predictions are based on a non-Hispanic white child, born in the United States, living in an attached house, built between 1960 and 1977, with smooth floors, no window replacement or cabinet or wall renovation, a household PIR of 1.1 (median for the data set), no smokers in the house, and simultaneously exposed to a sill dust loading of 6 µg/ft^2 (median). These characteristics describe the most typical child in the collected data that were used for modeling.

Table 3-2. Linear Model Results for Log Children's PbB[a] (Dixon et al. 2009)

Variables	Overall p-value	Levels	Coefficient (SE)	p-Value
Intercept	0.172		−0.517 (0.373)	0.172
Age (in years)	< 0.001	Age	2.620 (0.628)	< 0.001
		Age^2	−1.353 (0.354)	< 0.001
		Age^3	0.273 (0.083)	0.002
		Age^4	−0.019 (0.007)	0.008
Year of construction	0.014	Intercept for missing	−0.121 (0.052)	0.024
		1990–present	−0.198 (0.058)	0.001
		1978–1989	−0.196 (0.060)	0.002
		1960–1977	−0.174 (0.056)	0.003
		1950–1959	−0.207 (0.065)	0.003
		1940–1949	−0.012 (0.072)	0.870
		Before 1940	0.000	—
PIR	< 0.001	Intercept for missing	0.053 (0.065)	0.420
		Slope	−0.053 (0.012)	< 0.001
Race/ethnicity	< 0.001	Non-Hispanic white	0.000	—
		Non-Hispanic black	0.247 (0.035)	< 0.001
		Hispanic	−0.035 (0.030)	0.251
		Other	0.128 (0.070)	0.073
Country of birth	0.002	Missing	−0.077 (0.219)	0.728
		United States[b]	0.000	—
		Mexico	0.353 (0.097)	< 0.001
		Elsewhere	0.154 (0.121)	0.209
Floor surface/condition × log floor PbD	< 0.001	Intercept for missing	0.178 (0.094)	0.065
		Not smooth and cleanable	0.386 (0.089)	< 0.001
		Smooth and cleanable or carpeted	0.205 (0.032)	< 0.001
Floor surface/condition × $(\text{log floor PbD})^2$		Not smooth and cleanable	0.023 (0.015)	0.124
		Smooth and cleanable or carpeted	0.027 (0.008)	0.001
Floor surface/condition × $(\text{log floor PbD})^3$		Uncarpeted not smooth and cleanable	−0.020 (0.014)	0.159
		Smooth and cleanable or carpeted	−0.009 (0.004)	0.012
Log windowsill PbD	0.002	Intercept for missing	0.053 (0.040)	0.186
		Slope	0.041 (0.011)	< 0.001
Home-apartment type	< 0.001	Intercept for missing	−0.064 (0.097)	0.511
		Mobile home or trailer	0.127 (0.067)	0.066
		One family house, detached	−0.025 (0.046)	0.596
		One family house, attached	0.000	—
		Apartment (1–9 units)	0.069 (0.060)	0.256
		Apartment (≥ 10 units)	−0.133 (0.056)	0.022
Anyone smoke inside the home	0.015	Missing	0.138 (0.140)	0.331
		Yes	0.100 (0.040)	0.015
		No	0.000	—
Log cotinine concentration (ng/dL)	0.004	Intercept for missing	−0.150 (0.063)	0.023
		Slope	0.039 (0.012)	0.002
Window, cabinet, or wall renovation in a pre-1978 home	0.045	Missing	−0.008 (0.061)	0.896
		Yes	0.097 (0.047)	0.045
		No	0.000	—

[a] n = 2,155; R^2 = 40%. [b] Includes the 50 states and the District of Columbia.

Table 3-2 displays the table of model coefficients reported by Dixon et al (2009). Figure 3-2 uses that model to present the predicted geometric mean blood lead for different floor dust-lead values under three sets of assumptions or scenarios. The first scenario (or the "central tendency" scenario, CT) assumes, as above, a child aged 18 months, non-Hispanic white, born in the United States, living in an attached house, built between 1960 and 1977, with smooth floors, no window replacement or cabinet or wall renovation, a household PIR of 1.1 (i.e., above the poverty level), nonsmokers in the house, and exposed to a sill dust loading of 6 µg/ft^2 (median value). The second scenario is the same as the first except that the geometric mean blood lead is predicted for a non-Hispanic black child, to illustrate the effect of ethnicity on blood-lead predictions, if all other assumptions are the same. The third scenario (or "upper-end" scenario) includes some of the same assumptions as the CT, but replaces other factors associated with increased blood lead, including non-Hispanic black, born outside the United States, living in a mobile home with non-smooth floors and a smoker in the home. These descriptors reflect possible alternatives in the survey questions, as can be seen in Table 3-2.

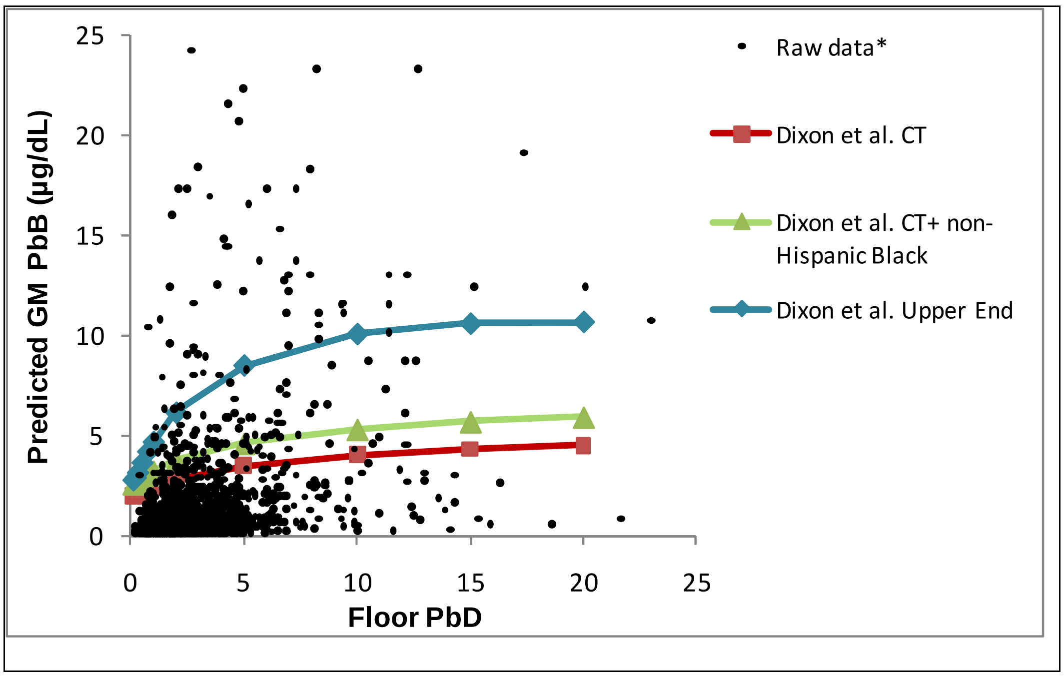

Figure 3-2. Predicted GM blood lead concentrations versus floor dust loading by scenario (See text for scenario definitions). (*Only raw data with PbB and/or Floor PbD values < 25 are shown for greater figure clarity.)

As shown in Figure 3-2, the overall form of the Dixon et al. model is strongly supra-linear at low floor-dust concentrations, and levels out above 15 µg/ft^2. Plotted in a natural scale, this behavior is a consequence of the log-to-log specification in the log-linear modeling. Also, the strong influence of the covariates can be seen in the large differences in predicted blood lead across the three scenarios.

3.1.2 NHANES Data Set

It should be noted that certain aspects of the NHANES data set present some challenges that cannot easily be overcome because they are inherent in the study design or are simply the results of the data as collected. NHANES was not originally developed for collection of environmental samples; however, the collection of blood lead data in tandem with dust lead samples from the children's homes provides a unique opportunity.

Additionally, although NHANES is a nationally representative sample of children 1 to 5 years old, the sample might not be representative of the U.S. housing stock. Some evidence suggests that the demographic and housing characteristics and blood-lead level distributions for the NHANES 1999–2004 sample might not be exactly representative of the U.S. population as a whole. Iqbal et al (2008) reported that missing blood-lead values are more common for relatively affluent non-Hispanic whites than for other groups.

The NHANES sampling protocol included only a single floor dust-lead measurement and single sill dust-lead measurement collected in the most visited room in the dwelling of the child participant. A more precise estimate of children's exposure would have been an average of several dust samples. In addition, 14 percent of floor dust loading samples and 36 percent of window sill loading samples are below the detection limit (0.16 µg for floors and 2 µg for sills). Dixon et al (2009) chose the common method of substitution with LOD/√2 (where LOD is level of detection). Although recommended by NHANES for use with its data, this approach, however, can skew the distribution and introduce bias in the regression estimates.

Only 1618 of the records in NHANES include sill dust measurements (of the 2155 records of blood lead measurements and 2065 records of floor dust lead loading measurements). Therefore, for use in a statistical model, the data must either be imputed for the missing (447) values or the records must be limited to just those with sill dust measurements, which is a smaller data set. A discussion of how this issue was handled is presented in Section 3.2.2.

3.2 Reanalysis of the 1999-2004 NHANES Data

EPA reanalyzed the 1999–2004 NHANES data to address certain aspects of the Dixon et al (2009) regression model that present obstacles to its use for evaluating blood-lead impacts of floor and sill dust lead hazard standards.

3.2.1 Model Development from Prediction of Children's Blood Lead from Residential Floor and Window-sill Dust Lead Loading

EPA considered the Dixon et al. (2009) log linear regression model linking log blood lead to log floor dust and log sill dust ("log-log model") not to serve its needs for prediction of blood lead from floor and sill dust loading for several reasons. Most importantly, the log-log form of the model:

$$\ln(PbB) = a + b_1 * \ln(\text{floor dust}) + b_2 * \ln(\text{sill dust}) + \sum (b_i * \text{covariates})$$

is supra-linear at low floor and sill dust loadings (see Fig. 3-2) and the predicted ln(PbB) is undefined when either value is zero.[1] Dixon et al (2009) recognized this shape, and explored some other data sets' relationships, but these sets had higher floor dust levels, lying in the more nearly linear portion of the curve, where the log nature is not as influential. The curvature of the model at high floor and sill dust levels appears to be driven by a few observations with extreme values (95 percent of the observations are at floor dust loadings < 4 µg/ft2 and sill dust loadings < 5 µg/ft2) (see Figure 1 in Dixon et al., 2009). In addition, the log-log model does not appear to be consistent with linear low-dose biokinetics (e.g., linear dependence of blood lead on lead dose under steady-state conditions), currently theorized to occur at low levels, that is supported by a large body of experimental and human data (USEPA 2006).

Floor-dust lead loading enters into the log-log model fit by Dixon et al. (2009) only in the form of interaction terms. For the Agency's reanalysis, models were explored where ln(floor-dust loading) was included both as a main effect and in the interaction terms. Finally, models were fit without intercepts representing missing data, to evaluate the impact on the predicted relationships between floor and window-sill dust loading and children's blood-lead levels.

Consistent with these considerations, several different models were evaluated, which, in addition to seeking to explain the maximum proportion of variability in blood lead, had the primary objectives of (1) fitting models that were consistent with the theorized linear low-dose biokinetics and (2) adequately accounting for the variance structure of the data.

With regard to the first concern, complications arise because the data collected in NHANES strongly suggest that the relationship between floor dust lead loading and blood lead is somewhat nonlinear at loadings below 10 $\mu g/ft^2$, despite the biokinetic prediction of low-dose linearity at steady-state exposures. These observations affect about 97 percent of the data. Figure 3-3 shows a plot of the smoothed relationship between floor-dust loading and blood lead for this portion of the data. Exploratory analyses indicated that this curvilinearity, although not as severe as suggested by the log-log model, is inherent in the dust lead-blood lead relationship in the NHANES data, and is not explained by other covariates (age, gender, ethnicity, housing variables, etc.). The relationship between sill-dust loading and blood lead is weaker than that for floor dust and determining the degree of nonlinearity, if any, is difficult.

The second concern (fitting the variance of the data adequately) was also difficult to address. Values not only of the dependent variable, but also of the two major predictors (floor- and sill-dust loading), are distributed in a manner (highly skewed with long tails at high values and standard deviations greater than their means) that is not consistent with normality. Indeed, the apparent log-normality of these variables provides a strong rationale for fitting log-log models. Because of these characteristics of the data, a linear least-squares regression fit to these data would not have residuals that are normally distributed (variance estimates would be unreliable) and would also be highly influenced by the extreme values in the tails of the data (model coefficients would be unstable and possibly biased). Thus, a robust and variance-adjusted approach to estimating the statistical relationship between floor and sill dust lead loading and blood lead was chosen.

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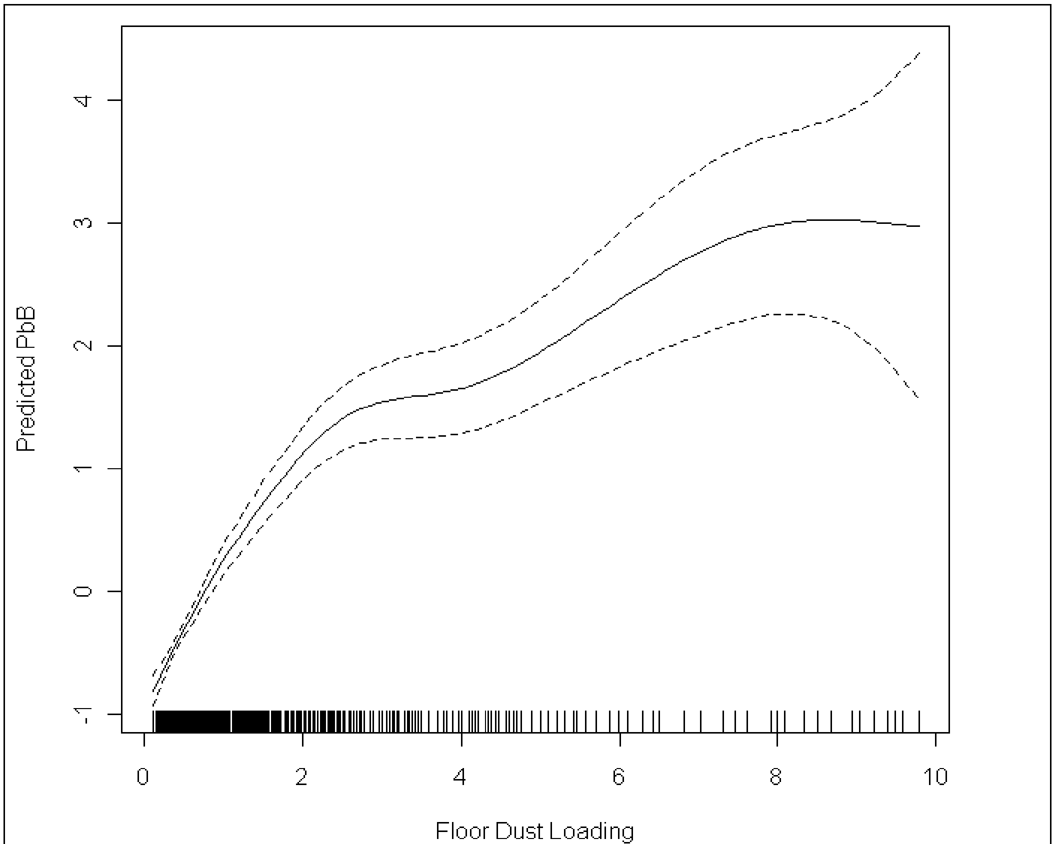
[1] The Dixon et al. regression model (Dixon et al., 2009) also predicts that blood-lead concentrations level off and then decline as floor-dust loading increases in the upper end of the range included in the NHANES data.



[a] with R *gam* package; smoothing function effective degrees of freedom = 4.5

Figure 3-3. Smoothed[a] relationship between floor dust- and blood-lead concentrations, 1999–2004 NHANES data, floor dust loading <10 µg/ft^2.

Based on the above considerations, a model was selected that (1) included exposure metrics as linear terms and (2) included an explicitly-fit variance term that was constrained to be proportional to the mean blood-lead level. A survey package (Lumley 2010) in R programming language was used to fit a quasi-likelihood generalized linear model (GLM) to the dust lead variables and covariates using a model design that took into account the stratification and clustering of the NHANES data.

3.2.2 Imputation of missing dust loading values

As mentioned in Section 3.1.2, of the 2,155 records in the NHANES data with blood-lead measurements, 2,065 also have recorded floor dust-lead loading measurements, while only 1,618 of the records also include sill dust measurements. Thus, if a statistical model is to be developed for estimating blood lead on the basis of floor and sill dust lead, it is necessary to either (1) limit the analysis to the 1,618 records with floor and sill dust and blood lead measurements (78 percent of the data) or (2) impute values for the 447 missing sill dust observations.

In their blood- lead regression, Dixon et al. (2009) chose to impute the missing values based on an unweighted regression that included only floor dust as an explanatory variable: ln(sill PbD) = 2.654 + 0.524 × ln(floor PbD). The correlation between sill and floor dust in records with both measurements was 0.38, implying that the proportion of variance explained by the regression (R^2) was approximately 0.14. Gaitens et al. (2009) also developed a linear regression that included covariates, but not floor dust loading. The model was adjusted for clustering and stratification. Coefficients were significant for ethnicity (the index child being non-Hispanic black), year of construction (older homes having higher sill dust levels), sill being not smooth and cleanable, presence of one or more smokers in the home, presence of a large area of chipped or damaged paint on the outside of a pre-1950 home, presence of damaged paint inside the house, and year in which the home was surveyed. The R^2 for the regression was 0.20 (corresponding to a correlation of 0.45). The reason for not including floor dust as a main effect in the model (e.g., whether in the presence of the other covariates it became nonsignificant) was not explained by Dixon et al. (2009). These approaches of dealing with missing values introduced an element of collinearity into the model that could have biased the regression coefficients and standard error estimates. That is, the sill-dust values in the model are actually just transformed floor-dust values, and thus are perfectly correlated with them.

For the Agency reanalysis, a regression model for sill dust was developed that included not only floor dust but also other significant covariates, assuming that such a model would explain more of the variance in the window-sill dust levels and thus provide a more reliable imputation of missing sill dust values. The linear multiple regression model was fit to the NHANES data using backwards stepwise methods based on varying F-to-include criteria, with a final criterion value of F = 5.0 used to allow variables to remain in the model. Parsimony of the model was also assessed using Mallow's C_p values (equivalent to a version of the Akaike Information Criterion as adapted for evaluation of least-squares models). The model was fit using the 1,004 records having valid observations for all the explanatory variables; estimates were not imputed for missing floor dust values or values of any covariates.

The final model, coefficients, and standard errors developed for this report are summarized in Table 3-3. Many of the variables Gaitens et al. (2009) identified were also significant contributors to this model, but their addition to the model with ln(floor dust loading) increased the proportion of variance explained (R^2) in ln (sill dust loading) to 0.253 (adjusted for the number of coefficients). In addition to floor dust loading, other variables for which the coefficients were significant include the index child being non-Hispanic black, having the sampled unit be a mobile home or apartment (as compared to a detached house), having a window sill that is not smooth and cleanable, having the sampled room classified as "dirty" by the surveyor, and having the unit surveyed in the second wave of NHANES sampling (2001–2002). The same statistically significant pattern of increasing sill dust loading with the earlier date of construction was observed as that reported by Gaitens et al. (2009). Figure 3-4 compares the window-sill dust values predicted by the regression model to the actual values for the 1,004 records used to fit that model.

Table 3-3. Regression Model Used to Impute Window-sill Dust Loading for Records with Missing Values[a]

Variable	Coefficient	Standard Error	t-statistic	p-level[b]
Intercept	1.616	0.135	11.98	$<10^{-6}$
ln(floor dust loading)	0.376	0.044	8.52	$<10^{-6}$
Non-Hispanic Black	0.327	0.118	2.77	0.006
Unit = Mobile Home	0.351	0.173	2.03	0.04
Unit = Apartment	-0.258	0.129	-2.00	0.05
Date of Construction 1978–1990	0.347	0.150	2.31	0.02
Date of Construction 1960–1977	0.492	0.146	3.37	0.0008
Date of Construction 1950–1959	0.853	0.172	4.97	0.000001
Date of Construction 1940–1949	1.034	0.225	4.59	0.000005
Date of Construction Pre-1940	1.422	0.169	8.42	$<10^{-6}$
Sill Smooth and Cleanable = No	0.707	0.171	4.15	0.00004
Room Dirty = Yes	0.354	0.138	2.57	0.01
Surveyed 2001–2002	-0.194	0.100	-1.95	0.05

[a] Adjusted R^2 = 0.253, standard error of the estimate = 1.469, F (12, 990) = 29.258

[b] *p*-values are not adjusted for multiple comparisons.

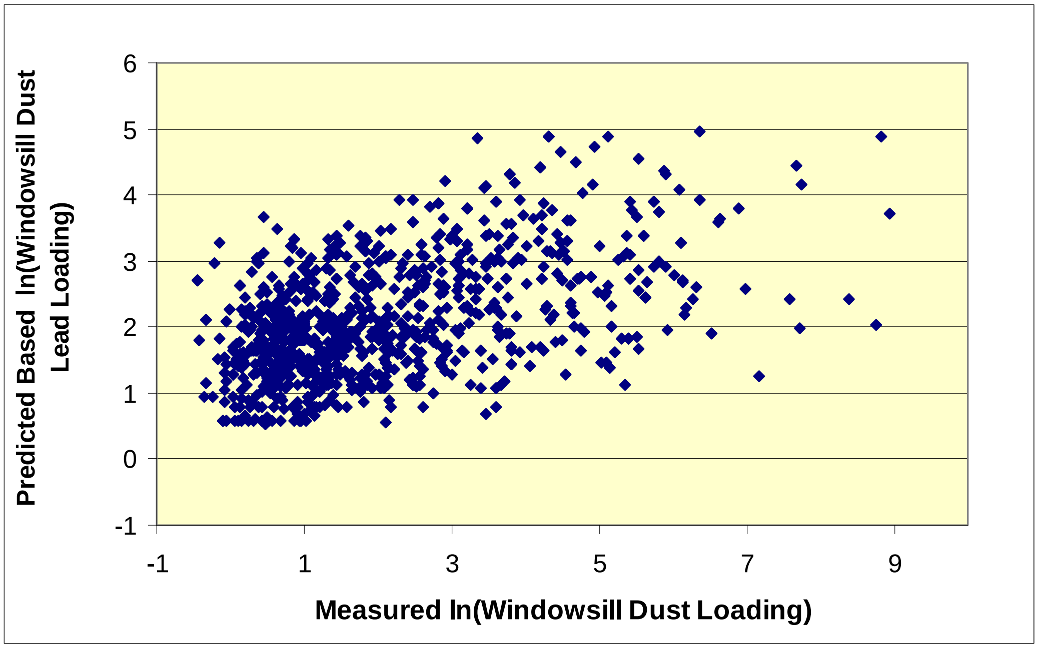


Figure 3-4. Comparison of predicted *versus* measured ln(window sill dust lead loading) (EPA reanalysis).

The window sill dust imputation model was tested for its sensitivity to how floor dust values below the limit of detection were treated; the raw data from NHANES include 259 observations where floor dust was "non-detect" and included as LOD/√2. When the records with below-LOD floor-dust values were omitted from the regression, the R^2 was reduced slightly to 0.248 and the coefficient for ln(floor dust) was increased from 0.376 to 0.418 ($p < 10^{-6}$). When below-LOD values were included at their respective LOD values, the R^2 was 0.257 and the ln(floor dust) coefficient was 0.437($p < 10^{-6}$). Detailed summaries of the window-sill dust regression analyses are provided in Appendix A.

3.2.3 Conversion of Dust Loading to Dust Concentration

Consistent with the desire to develop a dust lead-blood lead model, floor- and window-sill-dust lead loadings were first converted to estimated lead concentrations before they were entered into the model. This conversion was undertaken to transform the observations to a model consistent with linear low-dose biokinetics and to make the regression outcomes comparable with predictions from biokinetic models, which are discussed in the following sections. Despite the fact that relatively few data on the relationship between dust lead loading and dust lead concentrations are available, whenever biokinetic models are used to estimate children's blood lead from dust exposures, some method, either explicit or implicit, must be adopted to scale dust exposures based on loading to lead intake.

EPA analyzed the available evidence on the relationship between dust-lead loading statistics and dust-lead concentrations and developed two alternative methods for carrying out this conversion. The first, "the empirical approach," uses a regression relationship between dust-lead loading and dust-concentration measurements. The log-log model is fit to data from HUD's National Survey of Lead-Based Paint in Housing ("HUD Survey Data") that is provided in Appendix C-1 of EPA's risk assessment for TSCA section 403 (USEPA 1998). The survey measured floor dust loading (based on wipe samples) and dust concentrations (using Blue Nozzle vacuum sampling) in 312 homes selected to represent a nationally representative sample of housing characteristics. As described in Appendix E, a linear regression of ln(floor dust-lead loading) *versus* ln(floor dust-lead concentration), without covariates, had an R^2 of 0.465, and regression residuals were moderately close to being normally distributed about the mean ln(lead concentration) with no obviously nonlinearity. The regression equation, converted to exponential form, was:

$$\text{dust lead concentration, } \mu g/gm = 50.96 * (\text{dust lead loading, } \mu g/ft^2)^{0.6553}$$

Slightly improved fits could be obtained by including housing vintage (date of construction) in the model. For the dust lead-blood lead modeling, however, the model without covariates was used to estimate equivalent dust concentrations.

The extent of uncertainty associated with using this regression model is high and difficult to estimate precisely. Aside from questions about whether the dust loading and concentration values (measured in the mid-1990s) are still representative of U.S. housing stock, the wipe and Blue Nozzle methods may sample different size fractions of the house dust with differing efficiencies, thus biasing the observed relationship between loading and concentration. Alternatively, considering the many covariates that could affect dust loading and lead concentration, it is notable that the simple dust loading-dust concentration regression is significant and explains almost half the variance in the (logarithm of the) data. In addition, the log-log form of the relationship has a physical basis, assuming that the distribution of lead dust concentrations arises from random multiple dilutions of dust from multiple sources (Ott 1995).

In addition to the empirical model, a mechanistic model was also developed to characterize the relationship between household dust-lead loading and dust-lead concentration. The model simulates mass balance and transport processes for lead dust inside a hypothetical home, including the infiltration of suspended lead dust from outdoor (ambient) air, "track in" of exterior soils, and generation of particulates from lead-contaminated paint on indoor surfaces and other sources. Lead-contaminated particles are transported by settling and resuspension and are removed by cleaning (Figure 3-5).

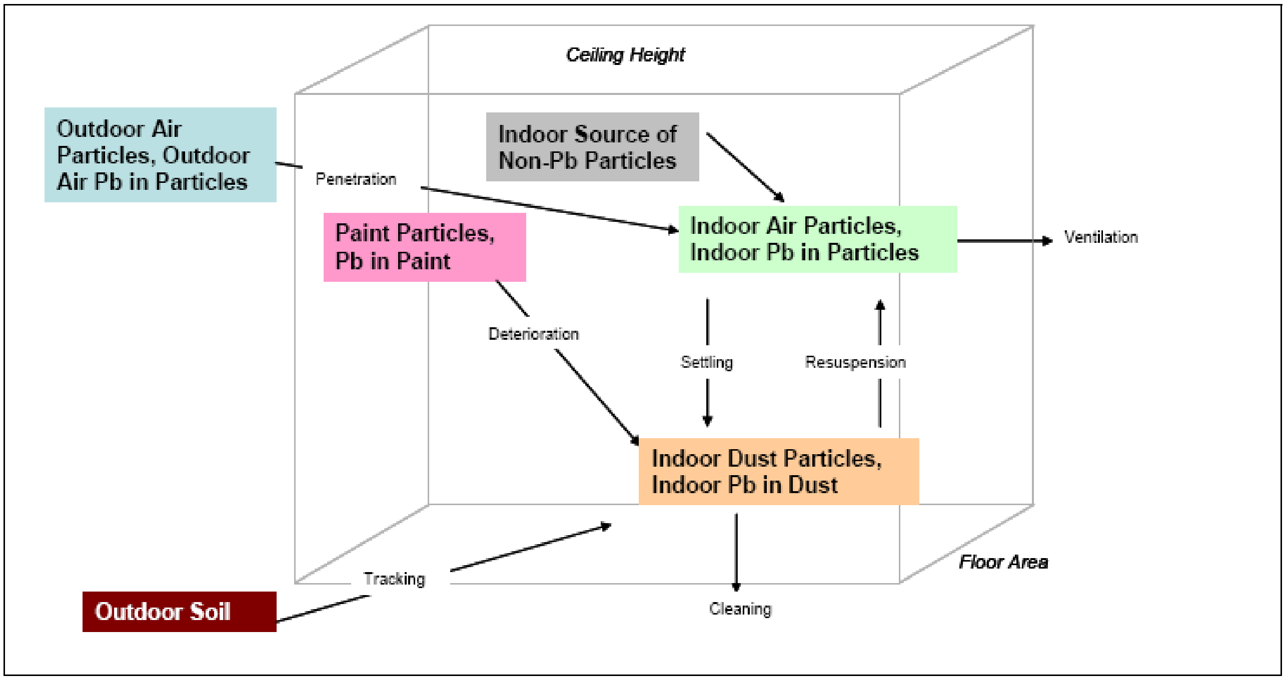


Figure 3-5. Mechanistic model for indoor dust generation, transport, and removal

Solving the differential equations representing all of the physical transport processes results in steady-state floor dust loading and concentration estimates that are functions of the rates of the various competing processes. A detailed discussion of the basis for selecting input variable values and a sensitivity analysis of model predictions is provided in Appendix E. When representative values of all inputs are used, the model predicts a linear relationship between floor dust lead loading and dust lead concentration:

dust lead concentration, µg/gm = 26.2 * dust lead loading, µg/ft^2.

As shown in Figure 3-6, the empirical and mechanistic models predict similar lead dust concentrations at relatively low floor dust loading (up to about 10 µg/ft^2), where most of the collected NHANES data lie. Above this level, the mechanistic model predicts higher values as the empirical model curves downward away from linearity.

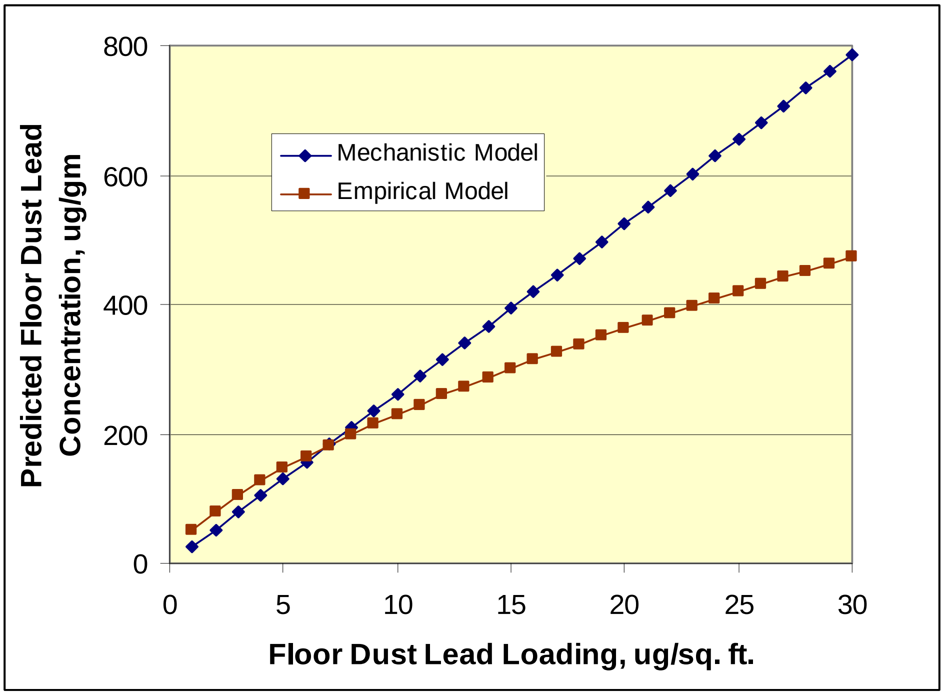


Figure 3-6. Comparison of dust lead concentrations predicted by the empirical and mechanistic models.

3.3 Regression Models for Children's Blood Lead

Quasi-likelihood generalized linear models were fitted to the dust lead-blood lead data and covariates from the 1999–2004 NHANES. The models were fitted to 2,055 records that had blood lead, floor dust lead loading, and sill dust lead loading measurements. Of these, sill dust measurements were imputed using the regression model described in Section 3.2.2. Models were developed using the R survey package by manual stepwise regression based on residual deviance. Individual variables were first tested for their contribution to deviance reduction, and then interaction variables were successively added to and removed from the model until the fit was no longer improved (variables that added more than approximately 0.5 percent to the total explained deviance were retained). Based on the findings of Dixon et al. (2009), powers of age up to the fourth power were tested. Floor dust and sill dust lead loading were included in the regression as equivalent lead concentrations, estimated using the empirical and mechanistic models described in Section 3.2.3. Note that using the linear mechanistic model estimates has the same effect, in terms of goodness of fit, as including the floor and sill dust loading measurements directly. The procedures used to derive the models are described in more detail in Appendix B.

Table 3-4 presents the coefficient values and goodness-of-fit metrics for the generalized linear models for children's blood lead. The same covariates were retained in the two models, regardless of whether dust concentrations were calculated based on the empirical or mechanistic models. In both cases, the coefficients for floor and window-sill dust (calculated) concentrations were significant at $p < 0.05$, with the coefficient for floor dust contributing more than that for sill concentration. When the empirical model was used, the coefficient for floor dust concentration was slightly more than 100 times that for window sill lead concentration. In the regression that used dust concentrations from the mechanistic model as its inputs, the coefficient for floor dust was approximately 700 times that for sill dust concentrations. These results provide additional support to the conclusion from previous studies and biokinetic modeling that sill dust has relatively little influence on children's blood-lead concentrations (as was used in the analyses that supported the 2008 Lead Renovation, Repair, and Painting Rule (USEPA 2008b)).

Table 3-4. Floor Dust Blood-lead Regression Results (Dust Concentration Based on Empirical and Mechanistic Models)

Coefficient	Empirical Dust Concentration Model[a]		Mechanistic Dust Concentration Model[b]	
	Value	p-value	Value	p-value
Intercept	0.41	0.44	0.85	0.12
Floor Dust Lead Concentration, µg/g	0.03[c]	$<10^{-6}$	0.02[d]	$<10^{-6}$
Sill Dust Lead Concentration, µg/g	0.00022[c]	0.026	0.00003[d]	0.021
Non-Hispanic Black (Race/ethnicity)	0.70	3.8E-06	0.79	1.8E-06
Age	0.14	0.017	0.15	0.013
Age^2	-0.0046	0.012	-0.0049	0.007
Age^3	0.000043	0.010	0.000045	0.006
Family Income Ratio to Poverty Level (PIR)	-0.16	$<10^{-6}$	-0.18	$<10^{-6}$
Year of Construction = pre-1940	0.49	0.013	0.66	0.004
Smoker(s) Present in House = yes	0.50	0.002	0.56	0.001
Floor Smooth and Cleanable = yes	0.27	0.099	0.24	0.089
Floor Dust Pb × Floor Smooth and Cleanable	-0.01[c]	0.014	-0.01[d]	0.005
Floor Dust Pb × Age	-0.00027[c]	0.002	-0.00026[d]	0.002

[a] Null deviance = 2,512, residual deviance = 1,605
[b] Null deviance = 2,512, residual deviance = 1,655
[c] Dust lead concentrations calculated based on empirical model
[d] Dust lead concentrations calculated based on empirical model

In addition to floor and sill dust, other variables that explained significant portions of the deviance[2] in the model were age up to the third power, family income compared to the poverty level, early (pre-1940) date of construction, and the presence of one or more smokers in the house. The coefficient for the floor's being smooth and cleanable essentially was significantly greater than zero (p = 0.099) for the empirical model but not the mechanistic one, but because the interaction between floor condition and floor dust concentration was significant both terms were retained in the models. One other interaction variable, representing floor dust concentration and age, was also significant and explained appreciable deviance in the model.

The age pattern of predicted blood-lead concentration is similar to that seen for the Dixon et al. (2009) model (Figure 3-7). The maximum blood-lead concentrations were predicted for the age range 18–24 months, based on a child who is not non-Hispanic black[3] and who lives in a house that was built after 1940 and has smooth and cleanable floors.

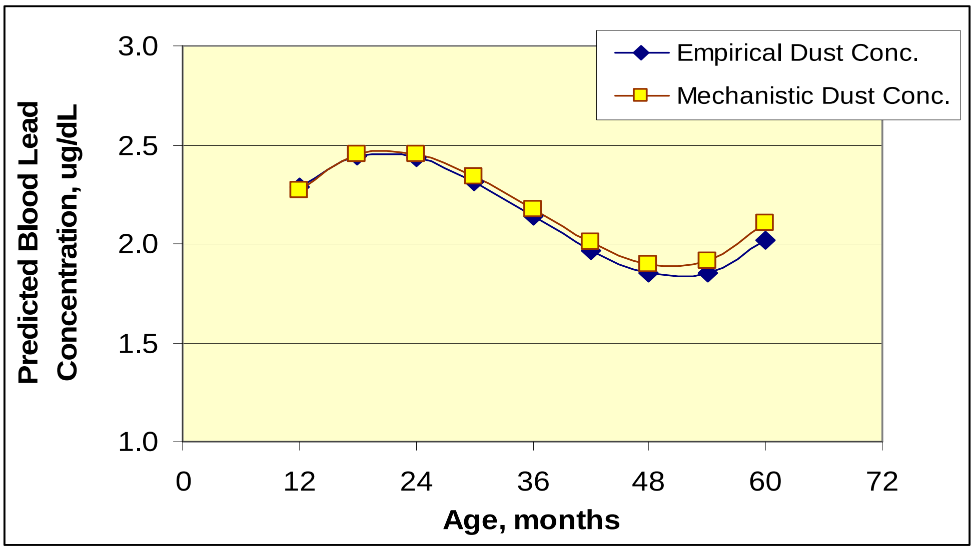


Figure 3-7. Predicted blood-lead concentrations *versus* age based on the quasi-likelihood model, central tendency scenario.[a]

[a]. Scenario = child is not non-Hispanic black, house built in or after 1940, no smokers present, smooth and cleanable floors.

Figure 3-8 compares the blood-lead concentrations predicted by the quasi-likelihood model with the observed blood-lead data. As was the case with the Dixon et al. (2009) regression, this comparison is not

[2] Other variables were found to be significantly related to blood-lead concentration but were not retained because they did not improve the fit of the model as judged by the proportion of deviance explained.

[3] Variables for the EPA model are derived from the NHANES survey questions slightly differently from those for Dixon et al. (2009) (see Appendix B). This scenario is the one corresponding to the central tendency scenario described in Section 3.1.1.

exact because the predicted values are based on an 18 month-old child, the window-sill dust is assumed to be at its median values, and only specific combinations of covariates are considered in the model predictions. In Figure 3-8 (as in Figure 3-7), "central tendency scenario" refers to a child 18 months of age who is not non-Hispanic Black, and who lives in a house built in 1940 or later that has smooth and cleanable floors, with no smokers present. An "upper-end scenario" refers to an 18-month-old non-Hispanic black child living in a pre-1940 house with floors that are not smooth and cleanable.

Consistent with theory, blood-lead predictions based on dust concentrations from the mechanistic model are linearly related to floor dust concentration, while predictions based on the empirical model are slightly curvilinear, reflecting the log-log form of the dust-lead loading-concentration regression. Blood-lead predictions are quite similar up to a floor dust loading of 20 µg/ft^2 from the two models under central-tendency scenarios, while the predicted blood lead based on an empirically-calculated dust concentration curves downward slightly at high dust loading values. Under the upper-end scenario, the differences in blood-lead predictions between the two dust concentrations become more pronounced as floor dust loading increases. As would be expected, the predicted blood-lead values are substantially higher under the upper-end scenario than under the central-tendency scenario. For the central-tendency scenario, the empirical dust-lead concentration model predicts blood-lead concentrations of 5.2 and 7.0 µg/dL at floor dust lead loadings of 10 and 20 µg/ft^2, respectively, while the corresponding predictions for the upper-end scenario are 6.5 and 8.6 µg/dL. Using the mechanistic model, the differences between loading-related predictions are even greater; under the central-tendency scenario, the predicted blood-lead concentrations are 5.1 and 8.0 µg/dL, at dust loadings of 10 and 20 µg/ft^2, while the corresponding predictions under the upper-end scenario are 8.1 and 12.7 µg/dL. As discussed further in Section 6, a large proportion of this difference is due to the effect of the strong interaction between floor dust concentration and floor condition in the quasi-likelihood regressions and to the effects of ethnicity and date of construction.

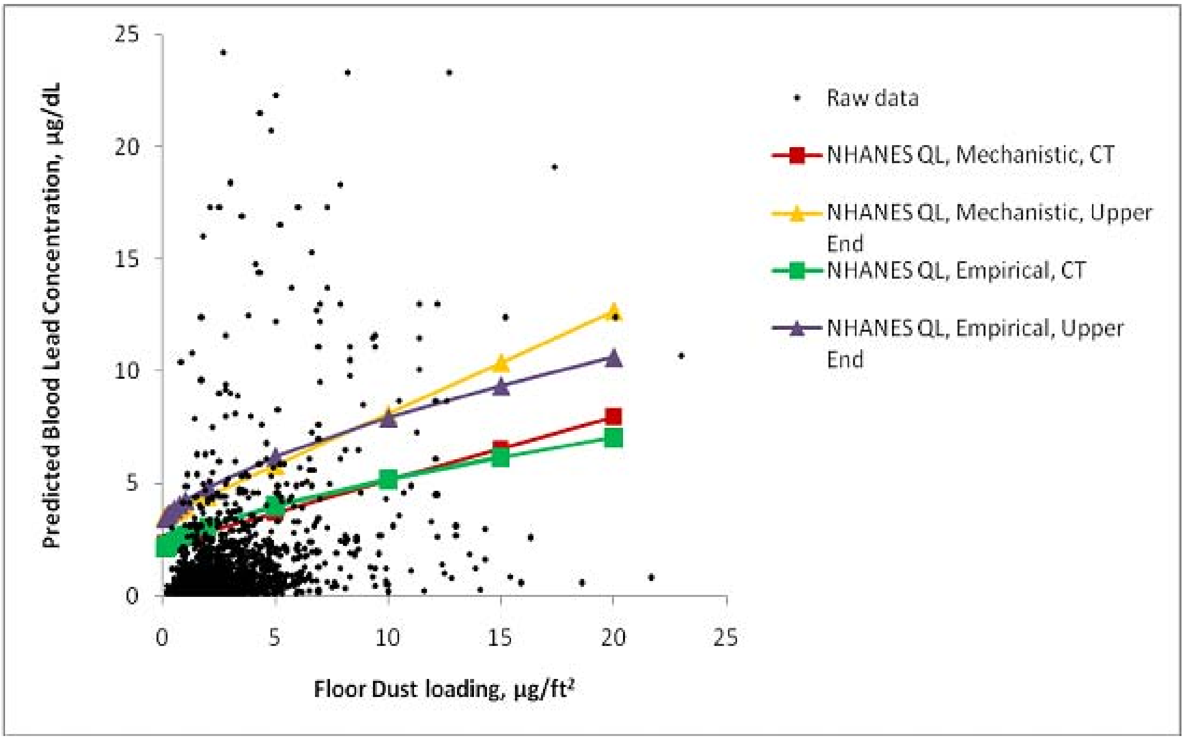


Figure 3-8. Comparison of predicted and measured blood-lead concentrations *versus* measured values, quasi-likelihood GLM based on floor dust loadings. (Only raw data with PbB and/or Floor PbD values < 25 are shown for greater figure clarity.)

4. Estimates of Blood Impacts Based on Biokinetic Models

The second method used to estimate floor and window sill hazard standards involved the use of two biokinetic models. The sources for the various input values for the biokinetic models are described below.

To determine where the newly developed empirical model results lay relative to underlying biokinetic theory, levels also were estimated using two well-validated biokinetic models. The IEUBK model (USEPA 2010c) was originally derived in the 1980s to estimate children's blood-lead impacts from exposures to lead in air and from multimedia lead contamination at hazardous waste sites. Since 1991, model development and updates have been overseen by the Technical Review Workgroup for Lead (TRW), led by the Office of Solid Waste and Emergency Response (USEPA 1994). The TRW continues to issue guidance on the use of the model and updated recommendations on appropriate values for specific model inputs.

The sources for the various input parameters for the biokinetic models are discussed in Sections 4.1.1-4.1.5, and the baseline values for non-soil and dust-related exposure factors are presented in Table 4-3. To run the IEUBK model, it is necessary to derive a weighted-average soil concentration for exposure at home, in child-occupied facilities, and in public/commercial buildings. For the baseline exposure scenario, soil concentrations from each microenvironment were weighted according to the amount of time spent in each microenvironment, as shown in Table 4-1. Also necessary is the derivation of an average dust concentration estimate based on the relative contributions of floor and window-sill dust. As discussed in Section 4.1.4, under the baseline exposure scenario, sill dust was assumed to contribute 1 percent of the total dust-lead intake, with the remainder provided by floor dust; the impact of this assumption on predicted blood-lead levels was evaluated through sensitivity analysis, as discussed in Section 6.

For the Leggett model, EPA developed a batch-mode "shell" to (1) calculate the total age-specific lead dose from multiple exposure pathways and (2) automate the evaluation of blood-lead impacts from multiple combinations of floor and sill dust. To afford comparability between the two biokinetic models, the Leggett shell was set up using exactly the same inputs as those for the IEUBK model. Thus, for any given exposure scenario, the biokinetic modules of the two models received identical age-adjusted absorbed lead doses as inputs.

4.1 Definition of Exposure Scenarios

The evaluation of blood-lead impacts was based on a set of generic exposure scenarios that incorporated not only soil and dust lead exposures, but also exposures from other sources. In addition, the exposure scenarios also allowed for the lead exposure to be apportioned across dust and non-dust sources.

4.1.1 Identification of Microenvironments for Dust/Soil Exposure

To analyze blood-lead impacts of the dust standards, simple exposure scenarios were used that included only those microenvironments (1) that account for a significant proportion of children's total lead intake, based on analyses discussed in USEPA (2006), (2) for which exposure data were available, and (3) that are relevant to the impacts evaluation of the hazard standards.

Three microenvironments meeting these requirements were included in the children's exposure scenarios: (1) residence (indoors and outdoors), (2) child-occupied facilities, and (3) public and commercial buildings. Although lead exposure can occur in other settings (e.g., inside vehicles), more complex scenarios were not evaluated based on a combination of one or more of the three considerations noted above.

4.1.2 Time Spent in Microenvironments

For soil and dust, the amount of exposure for each microenvironment was assumed to be proportional to the average time (hours per day) spent in the microenvironment. EPA estimated time spent in the various microenvironments based on data from the Consolidated Human Activity Database (CHAD) (USEPA 2003) and algorithms from the APEX model (USEPA 2008d).

Exposure profiles were developed using data from CHAD for the target population and algorithms from the APEX model. Developed by the EPA's National Exposure Research Laboratory, CHAD contains data collected from several studies designed to capture human activity patterns, and consists of one or more diaries of activities of each participant during the 24-hour period. It is commonly used in exposure assessment and provides required inputs to several EPA exposure models, such as HAPEM, SHEDS, and APEX[4]. Some applications of CHAD data in exposure assessments by EPA include the characterization of inhalation exposures in EPA's National Air Toxics Assessment (NATA) and numerous reviews of the National Ambient Air Quality Standards (NAAQS) for criteria pollutants. Among the various datasets available in CHAD, only the National Human Activity Pattern Study (NHAPS) dataset contains data from a nationally-representative sample. This study, sponsored by the EPA and conducted by the University of Maryland, contains responses from 9,386 participants collected between October 1992 and September 1994. Because it is deemed that NHAPS data may not be sufficient to generate a large enough sample of exposure profiles, other studies were also included to develop activity patterns of simulated individuals. These other studies contain data that is collected from the following specific geographic locations: Cincinnati, Ohio; Baltimore, Maryland; California children study; California adults and youth study; Denver, Colorado; Los Angeles, California; Valdez, Alaska; and Washington, DC.

To generate the activity pattern of a simulated individual for a one-year period, one needs to develop a composite diary from individual 24-hour diaries. A simple approach is to assume that the individual engages in same set of activities and spends same amount of time for an entire period characterized by a CHAD diary. For example, a randomly sampled weekday diary from CHAD can be assumed to be applicable for all weekdays for a simulated individual. While this approach may capture between-person variability in activity patterns in the targeted population, the variation in day-to-day activities of the simulated individual is not modeled. Consequently this approach may result in unrealistically large or small exposure times. Therefore, a probabilistic algorithm that can also capture day-to-day variation in the activity patterns of simulated individuals needs to be applied to develop composite diaries from individual 24-hour diaries.

The Air Pollutants Exposure Model (APEX) is a peer-reviewed EPA model that is used to assess inhalation exposure for criteria and toxic air pollutants. The APEX model currently incorporates two stochastic methods to develop composite diaries to evaluate inhalation exposure. The diversity-autocorrelation algorithm assembles multi-day diaries based on reproducing realistic variability in a user-selected key diary variable – the variable that is assumed to have dominant influence on exposure. This algorithm works by first creating diary pools from the CHAD data. A diary pool is a group of CHAD diaries that has a common diary variable that has significant effect on activity patterns. For example, diary pools can be created for each day type (weekday, weekend day) and season (summer, non-summer) because it is expected that the activities of target population significantly differ from weekday to weekend and between a summer day and a non-summer day. Once diary pools are created, each diary in the pool was assigned a rank, or "x-score," based on the key activity variable. The composite diary was then assembled based on the x-scores using the longitudinal diary assembly algorithm. This algorithm aims to

[4] HAPEM = Hazardous Air Pollutant Exposure Model; SHEDS = Stochastic Human Exposure and Dose Simulation Model; APEX = Air Pollutants Exposure Model.

reproduce the user-supplied statistics ***D*** and ***A*.** The ***D*** statistic quantifies the relative importance of within-person and between-person variances in the key activity variable. The ***A*** statistic quantifies the day-to-day autocorrelation, which characterizes the similarity in diaries from day to day. Additional details of this algorithm are presented in the APEX technical support document (USEPA 2008c).

The second algorithm, the Cluster-Markov algorithm, also stochastically generates composite diaries from individual 24-hour period diaries. This approach was developed to represent variability better in activity patterns among simulated individuals. It first groups the CHAD diaries into two or three groups of similar patterns for each of the 30 combinations of day type (summer-weekday, non-summer weekday and weekend), demographic group (males and females), and age groups (0-4, 5-11, 12-17, 18-64, 65+). Next, for each combination of day type and demographic group, category-to-category transition probabilities are defined by the relative frequencies of each second-day category associated with each given first-day category where the same individual was observed for two consecutive days. A composite diary of one year was constructed by first randomly selecting one daily activity pattern from each of the CHAD categories to represent that particular day type and demographic group. Finally, a sequence of daily activities for a one-year period was generated as a one-stage Markov chain process using the category-to-category transition probabilities.

To generate a sufficiently large number of profiles (on the order of tens of thousands), this approach will apply both of the above algorithms and evaluate them for their statistical properties. The algorithm that most adequately represents both the within-person and between-person variability will ultimately be applied to characterize the human activity patterns.

While the time spent by children under age 6 in residential buildings is of primary interest, their time spent in other microenvironments also contributes to overall lead uptake and therefore must be characterized. In this approach, time spent by children in the following microenvironments was estimated from CHAD data:

- Residences;
- Child-occupied facilities (COF);
- Outdoors;
- Traveling; and
- Public and commercial building

It was assumed that the time spent in public and commercial buildings includes any time spent in an indoor building environment that is not a residential building or a child-occupied facility, and was estimated from CHAD data by aggregating several location categories. Table 3-2 shows average, median, and 95th percentiles of times spent in these microenvironments from the CHAD data for the six children's age groups considered. Note that the CHAD data contain over 100 location descriptions. For this approach, these locations were aggregated into the five categories mentioned above. For example, the time spent traveling includes general travel, motorized travel, travel by walking, and waiting for bus, train, or other vehicle. Similarly, time spent in other building includes time spent in public buildings (e.g., libraries, museums), hospitals, and commercial buildings (e.g., grocery stores, restaurants).

The baseline exposure scenario estimates time spent in the home, in child-occupied facilities, and in public and commercial buildings based on the average values for 2- to 3-year-olds shown in Table 4-1.

Table 4-1. Estimates of Children's Time (Hours) Spent in Microenvironments (CHAD)

Age	Residence	COF	Outdoor	Travel	Public/Commercial Buildings
Average Time Spent					
0 – 1	21.32	0.45	0.51	0.81	0.81
1 – 2	20.81	0.53	1.00	0.82	0.76
2 – 3	19.96	0.73	1.40	0.95	0.84
3 – 4	19.56	1.01	1.44	0.96	0.94
4 – 5	18.96	1.38	1.66	0.92	0.99
5 – 6	18.15	2.17	1.73	1.03	0.84
Median Time Spent					
0 – 1	22.00	0	0	0.67	0
1 – 2	21.42	0	0.42	0.58	0
2 – 3	20.50	0	0.67	0.67	0
3 – 4	20.00	0	0.83	0.75	0
4 – 5	19.25	0	1.00	0.75	0
5 – 6	18.17	0	1.00	0.75	0
95th Percentile of Time Spent					
0 – 1	24.00	2.71	2.50	2.42	3.91
1 – 2	24.00	6.16	3.84	2.66	3.50
2 – 3	24.00	7.83	5.25	2.83	3.41
3 – 4	24.00	8.34	5.00	2.92	4.00
4 – 5	24.00	8.75	5.68	2.41	3.96
5 – 6	23.00	8.83	5.76	2.84	3.75

Based on these data, children in this age group spend an average of 83 percent of their time at home, 3.0 percent in child-occupied facilities, and 3.5 percent of their time in public and commercial buildings. The average total time spent per day in the three microenvironments is 21.5 hours. Because the other microenvironments are not included in this value, EPA normalized for 24 hours to proportions of time spent in 21.5 hours (assuming all dust exposure occurs in these three settings). This normalization yielded proportional contributions to total dust exposure of 92.7 percent from residences, 3.4 percent from child-occupied facilities, and 3.9 percent from public and commercial buildings.

4.1.3 Soil and Dust Exposure Metrics

The contributions of outdoor soils to total soil exposures were apportioned according to relative time spent in each microenvironment. For the baseline scenario, soil lead concentrations in all three microenvironments were set to 29.9 µg/gm (Table 4-2), the median soil-lead value for residential soil-lead measurements from the National Survey of Lead and Allergens in Housing (NSLAH, HUD 2002). Similarly reliable, nationally representative values of soil-lead concentrations near public and commercial buildings were not available, so the NSLAH value for residences was also used in the baseline scenario. As discussed in Section 6, analyses were conducted to test the sensitivity of the blood-lead model predictions to alternative soil-lead concentrations in the various microenvironments.

As presented in Table 4-2, the residential floor dust and sill dust exposure metrics were either derived directly from observations (empirical data) or were set equal to the hazard standard levels when blood-lead predictions were developed. For the baseline exposure scenario, floor and sill dust-lead loading estimates for child-occupied facilities were set to the average values reported in a survey of childcare centers (Westat 2003). As was the case for soil-lead concentrations, no nationally representative estimates of floor and sill dust lead loadings were available for public/commercial buildings, so for the baseline scenario, loading values were set equal to the survey-weighted medians from the 1999–2004 NHANES data from residences. As discussed in Section 6, because children spend so little time on average in public and commercial buildings, blood-lead predictions for all the models are only very weakly influenced by plausible changes in dust loading and concentration values.

Table 4-2. Estimated Soil, Floor, and Sill Dust Lead Concentrations in Microenvironments, Baseline Scenario

Microenvironment	Soil Lead Concentration, µg/gm	Loading, µg/ft^2		Concentration, µg/gm	
		Floor Dust	Sill Dust	Floor Dust	Sill Dust
Residential	29.9[a]	--[b]	--[b]	--[b]	--[b]
Child-occupied Facility	29.9	1.3[c]	20.5[c]	60.5[d]	368.8[d]
Public/Commercial	29.9	0.55[e]	6.0[e]	34.4[d]	166.9[d]

[a] Geometric mean soil concentration in residential areas (NSLAH, HUD 2002)

[b] Measured value or value established based on hazard standard

[c] Westat (2003) survey of childcare facilities, mean

[d] Converted from loading measurements using regression approach (see text)

[e] Median residential floor and sill dust loading measurements from NHANES (1999–2004) data.

4.1.4 Relative Contributions of Floor and Window-sill Dust to Lead Exposures

Little evidence is available concerning the relative contribution of sill and floor dust to total lead exposure and intake. The issue is complicated by the expected relationships among age, behavioral variables, and dust exposure patterns and by the expected correlation between sill and floor lead loading. Because empirical and biokinetic models generally support that toddlers (children less than 3 years old) are most sensitive to blood-lead impacts of dust exposure based on considerations of approximate relative response to changes in dust exposure (see later discussion) direct exposure to sill dust might not be expected to be an important source of exposure for this group. To the extent that window-sill dust acts as a source of highly contaminated dust that is subsequently transported to floors, however, its indirect impact on total exposures might not be negligible. For the baseline scenario, 1 percent of children's residential dust exposure was assumed to be window-sill dust and 99 percent to be floor dust based on relative area considerations. This apportionment echoes that used in the analyses that supported the 2008 Lead Renovation, Repair, and Painting Rule (USEPA 2008b). This assumption also was varied during the sensitivity analyses of the various models.

4.1.5 Background (Non-dust) Lead Exposures and Exposure Factors

The baseline scenarios for the biokinetic modeling included contributions from soil, water, and ambient air exposures, in addition to soil and dust. The baseline values used as inputs to the IEUBK and Leggett models are summarized in Table 4-3, along with the sources from which the values were estimated. Many of the values (age-specific time spent indoors at home, amount of soil and dust ingested, drinking water consumption) were derived from EPA's Child-Specific Exposure Factors Handbook (USEPA 2008c). Other baseline estimates (water, dietary, and soil/dust gastrointestinal absorption fractions, age-specific dietary lead intake) are based on previous EPA analyses presented in the Air Quality Criteria Document for Lead (USEPA 2006) and in support of revisions to the National Ambient Air Quality Standard for Lead (USEPA 2008a) or the Lead Renovation, Repair, and Painting Rule. (USEPA 2008b). The original sources of dietary intake estimates were the U.S. Food and Drug Administration's Total Diet Survey (FDA 2001) and food consumption data from NHANES III (CDC 1997). Estimates of the proportion of time children spend indoors at home were from the CHAD database, as discussed above (USEPA 2003), and estimated maternal blood lead at birth (a necessary input for the IEUBK model) was derived from EPA's analysis of blood-lead data for women 18–45 years old from the 2007–2008 NHANES.

Table 4-3. Baseline Input Values for the Biokinetic Model

Input	Child Age (years)								Source
	0–0.5	0.5–1	1–2	2–3	3–4	4–5	5–6	6–7	
Fraction of time spent in the home	0.82	0.82	0.79	0.77	0.76	0.73	0.7	0.69	CHAD Database (USEPA 2003)
Soil absorption fraction	0.3								USEPA (1994), USEPA (2008c)
Fraction of soil + dust intake that is soil	0.45								van Wijnen et al. (1990), USEPA (1989)
Dust + soil intake (g/day)	0.06	0.06	0.11	0.11	0.11	0.11	0.11	0.11	Child-Specific Exposure Factors Handbook (USEPA 2008c), excluding pica and geophagy
Dietary lead intake (mg/day)	3.16	3.16	2.6	2.87	2.74	2.61	2.74	2.99	LRRP Rule (USEPA 2008b)
Dietary absorption fraction	0.5								Alexander et al. (1974), Ziegler et al. (1978) cited in USEPA (2006, section 4.2.1)
Water consumption (L/day)	0.36	0.36	0.27	0.32	0.35	0.38	0.40	0.41	USEPA (2008b) with age interpolation
Water lead concentration (mg/L)	4.61								Geometric mean of studies in United States and Canada, USEPA (2006)
Water absorption fraction	0.5								Lead NAAQS (USEPA, 2008a) and LRRP Rule (USEPA, 2008c)
Ventilation rate (m^3/day)	5.4	5.4	8	9.5	10.9	10.9	10.9	12.4	USEPA (2008b) with age interpolation
Lung absorption fraction (unitless)	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	EPA (1989) Appendix A
Air concentration (mg/m^3)	0.01								AQS monitoring network for 2008 (USEPA 2010b)
Maternal blood lead (mg/dL)	0.847								NHANES 2007–2008, national weighted geometric mean of all women aged 18–45 (CDC 2009)

4.2 Analysis of Lead Dust Hazard Standards

EPA evaluated a range of hazard standards for floor and window-sill dust-lead loading. Because lead exposure and therefore predicted blood-lead concentrations are functions of both floor and sill dust exposures, each hazard standard consisted of a floor and a sill-dust-lead loading. EPA evaluated 20 combined floor and sill lead standards, combining floor dust-lead standards of 5, 10, 20, 30, and 40 μg/ft^2

with window-sill dust-lead loadings of 50, 100, 150, 200, and 250 µg/ft^2. For both floor and window-sill dust, the maximum loading values evaluated were the current proposed hazard standards. When biokinetic models were used to evaluate blood-lead impacts, the model inputs also included non-soil dust sources. When the empirical data were used as the basis for predicting blood-lead impacts, EPA assumed that the statistical models reflected the relationships between dust-lead and blood-lead levels, accounting for the appropriate covariates (including non-dust sources) by using a nationally representative sample of children (NHANES) and appropriately structuring the models.

4.3 Biokinetic Models

The intake module of the IEUBK model integrates exposures by inhalation of airborne particulates, diet, water, and soil and dust to derive estimates of total intake through inhalation and ingestion; default values for exposure factors (physiological and behavioral variables affecting lead intake) are included with the model, but can be changed by the user. Lead intake is converted to "uptake" (absorbed dose) by the use of respiratory, dietary, water, and soil/dust absorption fractions. The biokinetic portion of the IEUBK model consists of a central plasma/extracellular fluid compartment, with lead exchange, described by first-order rate constants, to and from trabecular and cortical bone, red blood cells, kidney, other soft tissues, and liver. Excretion in urine and feces and through skin and nails is also modeled. The IEUBK model is designed to estimate blood-lead levels in children aged 6 months to 7 years (84 months) based on defined exposure conditions and does not address the impacts of adult exposures.[5] The current version of IEUBK model runs on the Windows® operating system.

The IEUBK model has undergone extensive evaluation and validation by EPA scientists and outside reviewers (Mickle 1998), and the performance of the IEUBK, Leggett, and other biokinetic models was evaluated in detail in EPA's Air Quality Criteria Document for Lead (USEPA 2006). The IEUBK model has been used in support of a number of rulemaking efforts for water, air, and lead renovation and repair (USEPA 2008a,b) and other policy analyses related to children's lead exposures.

The Leggett biokinetic model was originally developed to evaluate the impacts of radionuclide exposures for the International Program on Radiological Protection (Leggett 1992, USEPA 2006). Unlike the IEUBK model, the Leggett model, as published, does not include modules for converting exposure in environmental media to absorbed dose. The user must add these features to the model if the model is to be used to evaluate environmental exposure scenarios.

The structure of the biokinetic modules of the Leggett model is more complex than that of the IEUBK model. Lead transport is modeled to and from a central compartment (plasma) and 15 other compartments, including the respiratory and digestive tracts, red blood cells, liver, kidneys, bone, brain, and "other soft tissue." The bone compartment is further divided into six subcompartments (cortical surface, exchanging volume and non-exchanging volume and trabecular surface, exchanging and non-exchanging volume) that differ in their biokinetic characteristics. Lead excretion through urine, feces, skin, sweat, and hair is also simulated. Unlike the IEUBK model, the Leggett model incorporates growth-curve data for the entire lifespan from birth through 75+ years and can therefore be used to estimate blood-lead impacts in adults and in children. Like the IEUBK model, the Leggett model accepts maternal blood lead as one of its inputs.

[5] Maternal blood-lead levels are required as inputs to the IEUBK model, but the model contains no fetal compartment, and blood-lead simulation begins at birth.

4.3.1 Biokinetic Model Inputs

To analyze multiple exposure scenarios (combinations of soil, dust, and "background" exposures), the batch-mode facility of the IEUBK model was used. Outputs from the batch runs were converted to spreadsheet form for analysis.

The Leggett shell was used to call an executable version of the Leggett model that was assembled from the FORTRAN model code, as provided by Dr. Joel Pounds (2006). A copy of the batch mode shell input page is provided in Appendix C.

4.3.2 Predicted Blood-lead Levels from Biokinetic Models

Neither the IEUBK model nor the Leggett model directly addresses the covariates included in the empirical models of blood-lead impact (ethnicity, income, surface quality, date of construction). The baseline scenarios evaluated using the biokinetic models include only those variables that directly affect lead exposures and intake. Thus, direct comparisons of the blood-lead predictions based on empirical and biokinetic models are not possible, although the intent of the baseline scenario is to select inputs that are "typical" and representative of national average values. Figure 4-1 shows the pattern of blood lead with age predicted by the IEUBK and Leggett models, using baseline non-dust exposure inputs, at a residential floor dust-lead loading of 0.55 µg/ft^2 and window-sill dust-lead loading of 6 µg/ft^2. (For input to the biokinetic models, these values were converted to equivalent floor and window-sill dust-lead concentrations of 34 and 165 µg/g, respectively.)

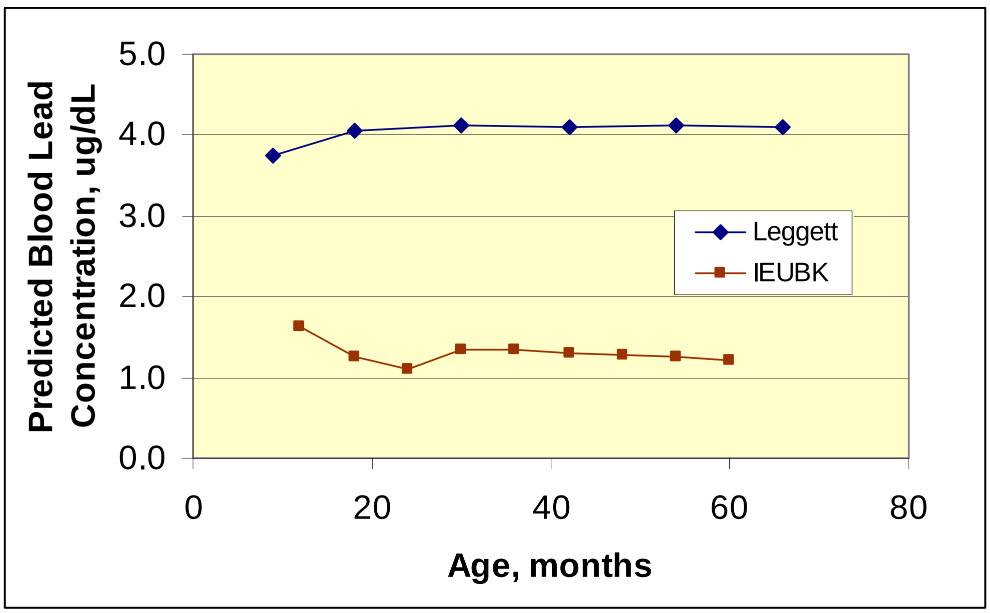


Figure 4-1. Age patterns of blood-lead predictions by the IEUBK and Leggett models (median floor and window-sill dust loading).

Figure 4-1 shows that both the predicted blood concentrations and the age variation of blood lead differ for the two models. The IEUBK model predicts geometric mean blood-lead values on the order of 1.1–1.6 µg/dL with a maximum of 1.62 µg/dL occurring at the age of 12 months with a pronounced dip at age 18–24 months. The main reason for this behavior appears to be that the estimated dietary lead intake and drinking water ingestion drop substantially between the ages of 1 and 2 years (see Table 4-3) and this drop in lead intake is not offset by the estimated increase in dust and soil ingestion that occurs during the same age range.

The blood-lead level predicted by the Leggett model using the same inputs is much higher, increasing from a low value of 3.75 µg/dL at 9 months to around 4.1 µg/dL at ages greater than 2 years. Because the age-specific lead intakes are the same, the differences in age patterns must be the result of differences in biokinetics between the two models.

Figure 4-2 shows the geometric mean blood-lead concentrations that are predicted by the two biokinetic models at median sill dust loading for floor-dust loading in the range of 0 to 20 µg/ft^2. For the IEUBK model, the values are shown for a 12-month-old (the maximum over the range examined), while for the Leggett model, the blood-lead predictions are provided for 18-month-olds. The data from the 1999–2004 NHANES are presented for comparison.

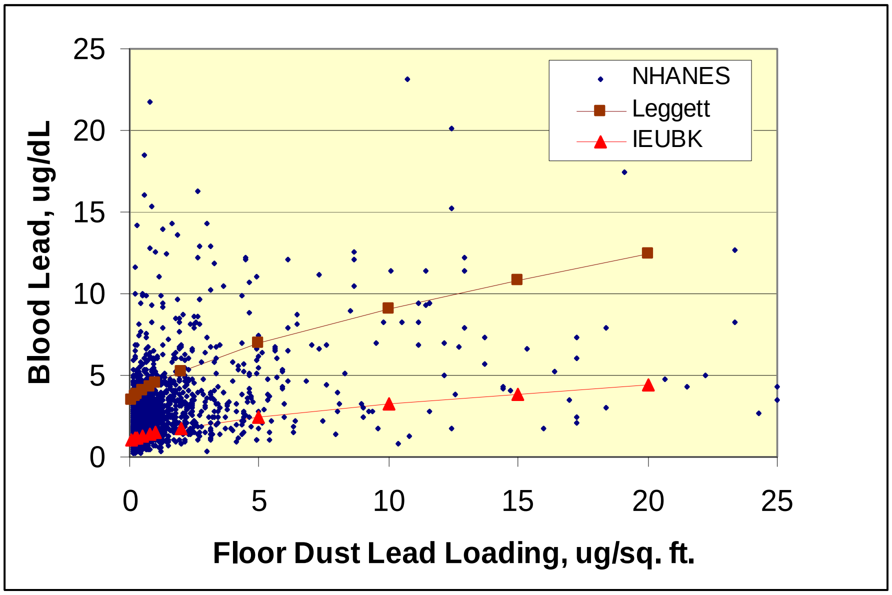


Figure 4-2. Blood-lead concentrations predicted by the IEUBK and Leggett models as a function of floor dust lead loading (median window-sill dust lead loading).[a]

[a] Blood-lead predictions from the IEUBK model are for children aged 12 months; for Leggett, 18 months.

The concentrations predicted by the Leggett model are, again, substantially higher than those predicted by the IEUBK model. The Leggett predictions range from 3.5 µg/dL at a floor dust-lead loading of 0.1 µg/ft^2 to 12.4 µg/dL at a floor dust loading of 20 µg/ft^2. The corresponding range for the IEUBK is 1.1 to 4.4 µg/dL. As discussed in the following sections, the geometric mean blood lead for U.S. children appears much closer to the IEUBK baseline predictions at low dust loading than to the predictions from the Leggett model.

5. Predicted Blood Lead Levels

5.1 Predicted Blood-lead Levels Associated with Candidate Dust-Loading Hazard Standards

Figure 5-1 shows the predicted blood-lead concentrations for the most sensitive age groups using the empirical (NHANES-based, evaluated at low floor - 0.1 μg/ft^2 - and sill - 6 μg/ft^2 - loading values) and biokinetic models (IEUBK and Leggett, evaluated at the values shown in Table 2-3). The predictions vary widely across the range of floor-dust loading from 0 to 20 μg/ft^2 at median sill dust concentrations. The IEUBK and Dixon et al. (2009) central-tendency regression results predict the lowest blood-lead concentrations across the entire range of dust loading, whereas the Leggett model and upper-end NHANES Quasi-Likelihood model based on mechanistically-modelled dust concentrations predict the highest concentrations at high dust loading. The Dixon et al. (2009) regression model evaluated at factors predisposing to higher blood lead ("upper end") does predict relatively high blood-lead levels in the range of about 2–10 μg/ft^2, which then flatten out at higher concentrations.

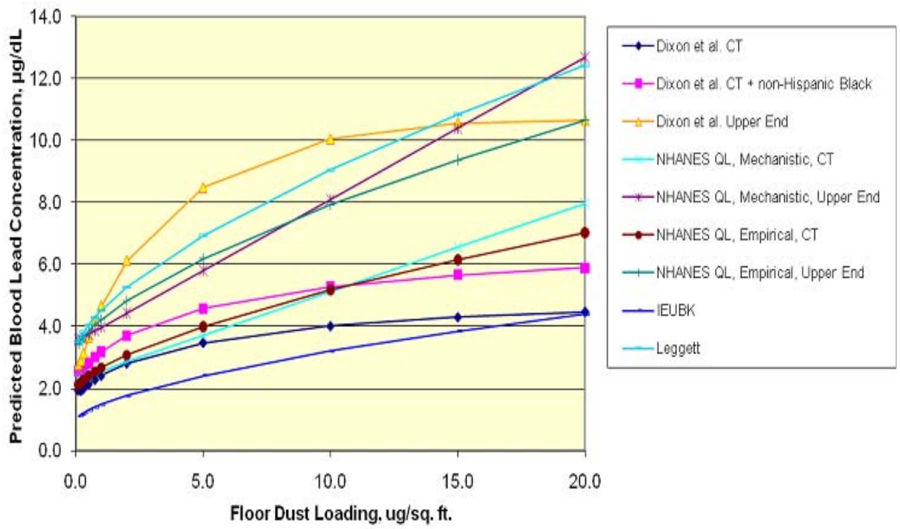


Figure 5-1. Predicted blood-lead concentrations as a function of floor dust lead loading.[a]

[a] Sill Loading = 6 μg/ft^2, age of children = 18 months, except for IEUBK (12 months); modeling scenarios as described in the text.

Table 5-1, part A, shows blood-lead predictions that can be characterized as a "background" value from each model. For the regression models, the results are simply the predicted blood-lead concentrations at low floor (0.1 μg/ft^2) and low sill (6 μg/ft^2) loading values. For the biokinetic models, the results are "baseline" estimates that include typical exposures from non-dust and non-soil sources, as discussed in Section 2.6.

Included in Table 5-1, part B, for comparison are survey-weighted geometric mean blood-lead concentration data for different survey years since 2000. As shown in Table 5-1, part A, the background blood-lead predictions from some models are in the range of national geometric mean values. The prediction from the IEUBK model (1.1 μg/dL) is somewhat lower than recently representative blood-lead concentrations, while the Dixon et al. and NHANES QL models predict background blood-lead concentrations that are more consistent with the recent NHANES geometric mean values, in keeping with the data on which those models are based. The upper-end regression models and the Leggett model predict background blood-lead concentrations that are somewhat greater than representative national values from 2000–2008.

Table 5-1. Predicted Blood-lead Concentrations at “Baseline” and NHANES Geometric Mean Values for 1- to 5-Year Olds

A. Predicted Concentrations at “Baseline”

Model	Predicted "Background" PbB, µg/dL
IEUBK	1.1
Dixon et al. CT	1.9
NHANES QL, Empirical, CT[a]	**2.1**
NHANES QL, Mechanistic, CT	2.3
Dixon et al. CT + non-Hispanic Black	2.6
Dixon et al., Upper End	2.8
NHANES QL, Empirical, Upper End	3.4
Leggett	3.5
NHANES QL, Mechanistic, Upper End	3.6
B. NHANES Geometric Mean Values, Children Aged 1–5 Years[b]	
1999–2000	2.3 (3.0)
2001–2002	1.8 (2.2)
2003–2004	1.9 (2.3)
2005–2006	1.5 (1.7)
2007–2008	1.7 (1.9)

[a] This is the model used in Section 5.2.
[b] Source = Analysis of NHANES data, numbers in parentheses are survey-weighted geometric standard deviations.

Blood-lead concentrations were estimated for a broader range of hypothetical dust-lead hazard standards than those corresponding to this report’s three candidate levels, covering floor dust loadings from 5 to 40 µg/ft^2 and window-sill dust loading levels from 50 to 250 µg/ft^2. Tables 5-2 through 5-4 summarize the results of the blood-lead modeling from the Dixon et al. regressions, the NHANES QL empirical models, and from the biokinetic models, respectively. The results are expressed as point estimates; for the log-linear Dixon et al. (2009) regression and the Leggett and IEUBK models, the estimates are geometric mean values. For the NHANEs QL regressions, the estimates are survey-weighted means, adjusted for dependence of variance on blood-lead values. In the discussions that follow, these point estimates are treated as if they were population geometric means.

The blood-lead predictions from the various models for the different hazard standards parallel the general pattern observed in Figure 5-1, with IEUBK and central-tendency Dixon et al. (2009) predicting the lowest geometric mean values, and the Leggett, upper-end NHANES QL, and Leggett predicting the highest values. A striking feature of this analysis is that the predicted geometric means from all models appear to exceed the lowest target blood-lead concentration (1 µg/dL), even at the most stringent candidate standard evaluated (floor = 5 µg/ft^2 and sill dust loading = 50 µg/ft^2. All of the predicted geometric mean blood-lead concentrations also exceed the next higher blood-lead target of 2.5 µg/dL, except the GM from the IEUBK baseline model, which is 2.4 µg/dL.

Predicted geometric mean blood-lead concentrations are much higher for candidate hazard standards at higher levels of floor and sill dust loading; all of the models predict geometric mean blood-lead levels above the highest blood-lead target evaluated (5 µg/dL), and most predict blood-lead levels above 10 µg/dL). Thus, most of the models used, even those predicting the lowest values for given levels of floor and sill dust loading, predict that a large majority of children in the age range of 1–2 years would have blood-lead concentrations above the target blood-lead levels (see below.)

Table 5-2. Predicted Geometric Mean Blood-lead Concentrations Associated with Candidate Residential Dust Lead Hazard Standards, Based on the Dixon et al. (2009) Regression Model

Dixon et al. Regression, CT Scenario					
Floor Dust Loading, µg/ft^2	Window-sill Dust Loading, µg/ft^2				
	50	**100**	**150**	**200**	**250**
5	3.8	4.4	4.9	5.1	5.2
10	3.9	4.5	5.0	5.2	5.3
20	4.0	4.6	5.1	5.3	5.4
30	4.0	4.6	5.2	5.4	5.5
40	4.1	4.7	5.2	5.4	5.5
Dixon et al. Regression, CT Scenario + nhBlack					
Floor Dust Loading, µg/ft^2	**Window-sill Dust Loading, µg/ft^2**				
	50	**100**	**150**	**200**	**250**
5	5.0	5.8	6.4	6.7	6.8
10	5.1	5.9	6.6	6.9	7.0
20	5.2	6.0	6.7	7.0	7.1
30	5.3	6.1	6.8	7.1	7.2
40	5.3	6.2	6.9	7.2	7.3
Dixon et al. Regression, Upper-End Scenario					
Floor Dust Loading, µg/ft^2	**Window-sill Dust Loading, µg/ft^2**				
	50	**100**	**150**	**200**	**250**
5	8.1	9.6	10.2	9.9	9.3
10	8.4	9.9	10.5	10.2	9.6
20	8.5	10.1	10.7	10.4	9.8
30	8.6	10.2	10.8	10.5	9.9
40	8.7	10.3	10.9	10.6	10.0

Table 5-3. Predicted Geometric Mean Blood-lead Concentrations Associated with Candidate Residential Dust Lead Hazard Standards, Based on the NHANES Quasi-likelihood Regression Model

NHANES QL Model (Empirical Dust Conc.), CT Scenario					
Floor Dust Loading, µg/ft^2	Window-sill Dust Loading, µg/ft^2				
	50	100	150	200	250
5	4.1	4.2	4.2	4.3	4.4
10	5.3	5.4	5.4	5.5	5.5
20	7.1	7.2	7.3	7.3	7.4
30	8.7	8.7	8.8	8.9	8.9
40	10.0	10.1	10.2	10.2	10.3
NHANES QL Model (Mechanistic Dust Conc.), CT Scenario					
Floor Dust Loading, µg/ft^2	Window-sill Dust Loading, µg/ft^2				
	50	100	150	200	250
5	3.7	3.8	3.8	3.9	3.9
10	5.2	5.2	5.3	5.3	5.3
20	8.0	8.1	8.1	8.1	8.2
30	10.8	10.9	10.9	11.0	11.0
40	13.7	13.7	13.8	13.8	13.9
NHANES QL Model (Empirical Dust Conc.), Upper End Scenario					
Floor Dust Loading, µg/ft^2	Window-sill Dust Loading, µg/ft^2				
	50	100	150	200	250
5	6.0	6.1	6.2	6.2	6.3
10	7.7	7.8	7.9	7.9	8.0
20	10.5	10.6	10.6	10.7	10.7
30	12.7	12.8	12.9	12.9	13.0
40	14.8	14.8	14.9	15.0	15.0
NHANES QL Model (Mechanistic Dust Conc.), Upper End Scenario					
Floor Dust Loading, µg/ft^2	Window-sill Dust Loading, µg/ft^2				
	50	100	150	200	250
5	5.8	5.9	5.9	6.0	6.0
10	8.1	8.2	8.2	8.3	8.3
20	12.7	12.8	12.8	12.8	12.9
30	17.3	17.3	17.4	17.4	17.5
40	21.9	21.9	21.9	22.0	22.0

Table 5-4. Predicted Geometric Mean Blood-lead Concentrations Associated with Candidate Residential Dust Lead Hazard Standards, Based on the IEUBK and Leggett Biokinetic Models

IEUBK Model, Baseline Scenario					
	Window-sill Dust Loading, µg/ft^2				
Floor Dust Loading, µg/ft^2	50	100	150	200	250
5	2.4	2.5	2.6	2.7	2.7
10	3.1	3.2	3.3	3.3	3.4
20	4.2	4.3	4.3	4.4	4.4
30	5.1	5.2	5.2	5.2	5.3
40	5.9	5.9	5.9	6.0	6.0
Leggett Model, Baseline Scenario					
	Window-sill Dust Loading, µg/ft^2				
Floor Dust Loading, µg/ft^2	50	100	150	200	250
5	7.1	9.2	12.5	15.3	17.8
10	7.2	9.3	12.6	15.4	17.9
20	7.2	9.4	12.7	15.5	18.0
30	7.3	9.4	12.8	15.6	18.1
40	7.4	9.5	12.9	15.7	18.1

5.2 Predicted Proportions of Children above Target Blood-lead Levels

Table 5-5 shows the pattern of proportions of children with blood lead above the specified target blood-lead levels predicted by the NHANES quasi-likelihood central-tendency regression using empirical dust concentrations, assuming that blood-lead distributions are log-normally distributed with a geometric standard deviation (GSD) of 2.1. This GSD value is derived as a central-tendency estimate as roughly in the middle of GSDs since the year 2000 in the analysis of recent NHANES data shown in Table 5-1. Showing the proportions exceeding (or less than) selected specified levels (in this case, the targets aimed at candidate lead dust hazard standards) is another way of conveying the variability in the population being studied. Different GSDs could be used with different descriptive assumptions. Consistent with the results shown in Table 5-3, large proportions of children in the central tendency group are predicted to have blood-lead concentrations above the target across the entire range of candidate hazard standards: between 40 and 83 percent above 5 µg/dL, between 75 and 97 percent above 2.5 µg/dL, and between 97 and 100 percent above 1 µg/dL. Tables of proportions for GSDs 1.9 and 2.3 are shown in Appendix D as are tables for the other models (e.g., Dixon et al., 2009).

Table 5-5. Proportions of Children Predicted by NHANES QL Central Tendency Regression Model, using Empirical Dust Concentrations, Blood-lead GSD = 2.1, to be above Target Blood lead levels.

Predictions based on NHANES QL Model (Empirical Dust Conc.), CT Scenario

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	40%	40%	41%	42%	43%
10	53%	54%	54%	55%	55%
20	68%	69%	69%	70%	70%
30	77%	77%	78%	78%	78%
40	83%	83%	83%	83%	83%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	75%	76%	76%	77%	77%
10	84%	85%	85%	85%	86%
20	92%	92%	92%	93%	93%
30	95%	95%	96%	96%	96%
40	97%	97%	97%	97%	97%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	97%	97%	97%	98%	98%
10	99%	99%	99%	99%	99%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

The same pattern is observed for the other models, as illustrated in Figures 5-2 and 5-3. These figures show the predicted proportions of blood-lead concentrations above 5 and 2.5 μg/dL, respectively, for the subset of potential hazard standards with floor dust loading of 5 $\mu g/ft^2$ and window-sill dust-lead loading ranging from 50 to 250 $\mu g/ft^2$, again assuming a blood-lead GSD of 2.1. A figure for the proportions of children above 1 μg/dL would be uninformative, as almost all models predict proportions greater than 95 percent above this level "across the board."

Figures 5-4 and 5-5 illustrate the variation in the proportions of children predicted to have blood-lead concentrations above 5 and 2.5 μg/dL, respectively, when different assumptions are made relating to the variability in blood-lead levels about the geometric mean. For the subset of models depicted, varying the estimated blood-lead GSD between 1.9 and 2.3 has only moderate impacts on the predicted proportions of children with blood-lead levels above the target. This issue is discussed further in Section 6.

Tables of geometric mean blood-lead values and estimated proportions of children with blood-lead concentrations above target levels are provided for all the models in Appendix D.

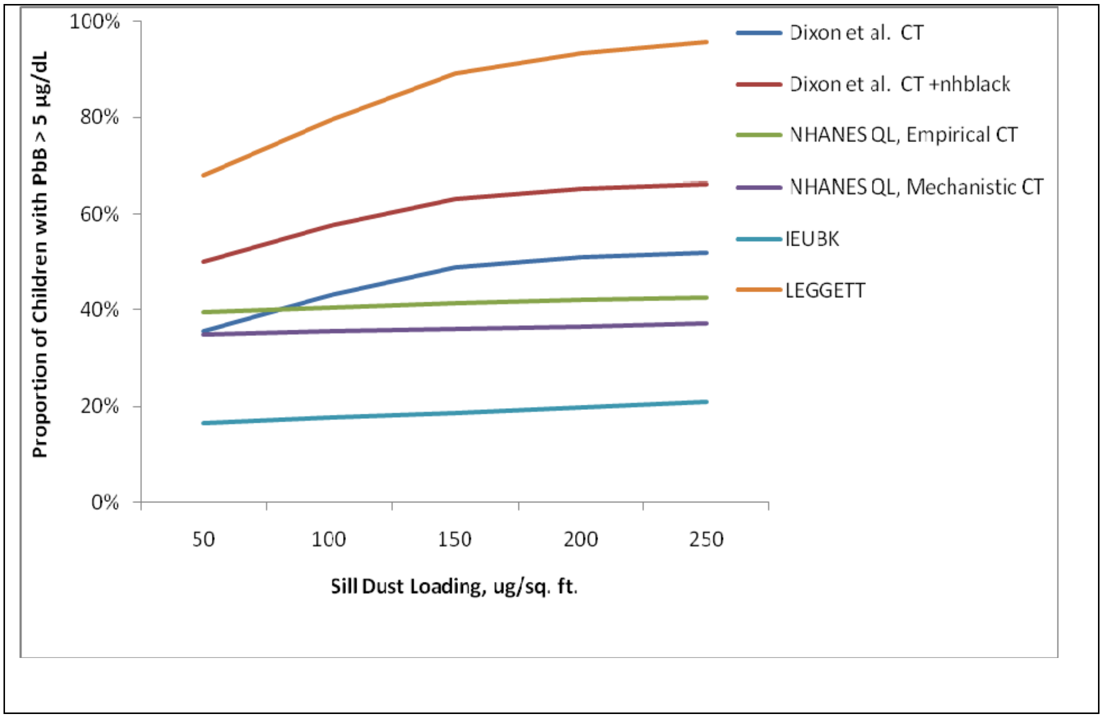


Figure 5-2. Predicted proportions of children with blood-lead concentrations greater than 5 µg/dL (floor dust lead loading 5 µg/ft^2, blood-lead GSD = 2.1).

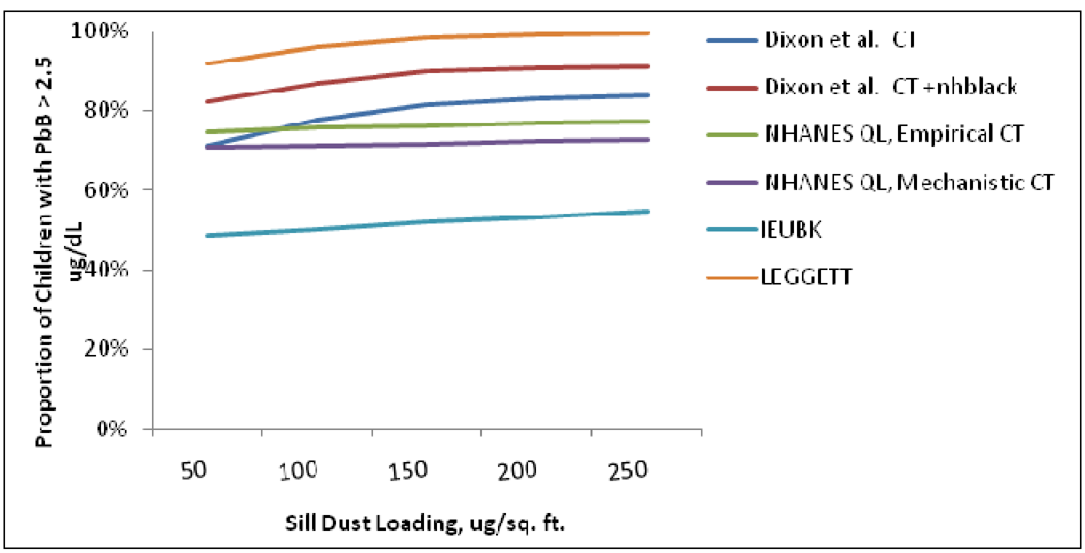


Figure 5-3. Predicted proportions of children with blood-lead concentrations greater than 2.5 µg/dL (floor dust lead loading 5 µg/ft^2, blood-lead GSD = 2.1).

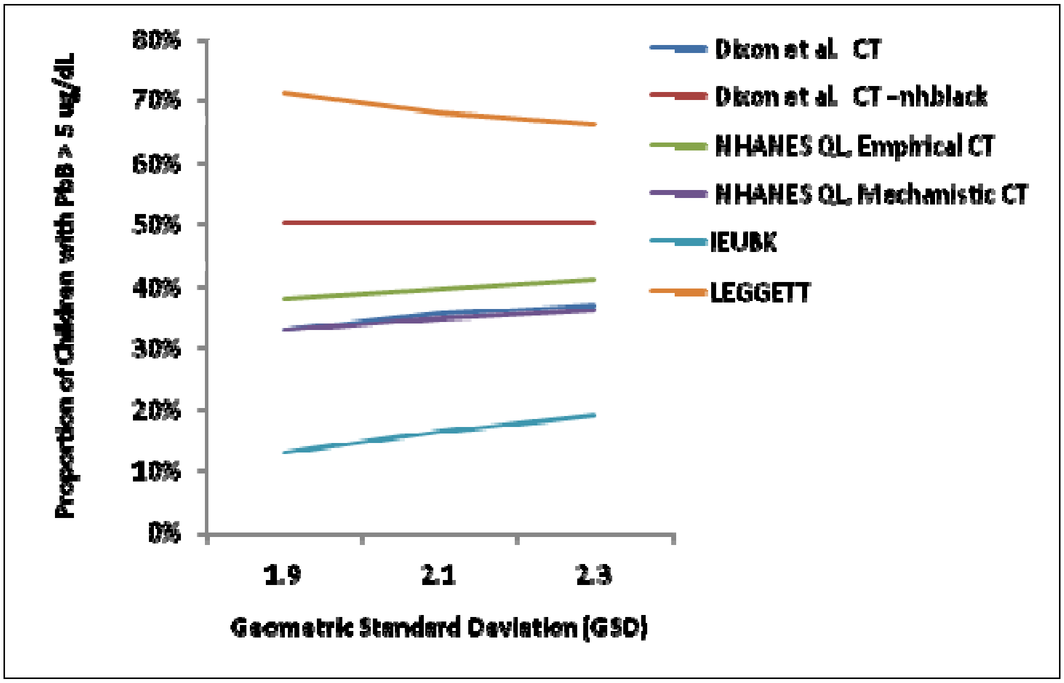


Figure 5-4. Predicted proportions of children with blood-lead concentrations > 5 µg/dL (floor dust loading 5 µg/ft^2)

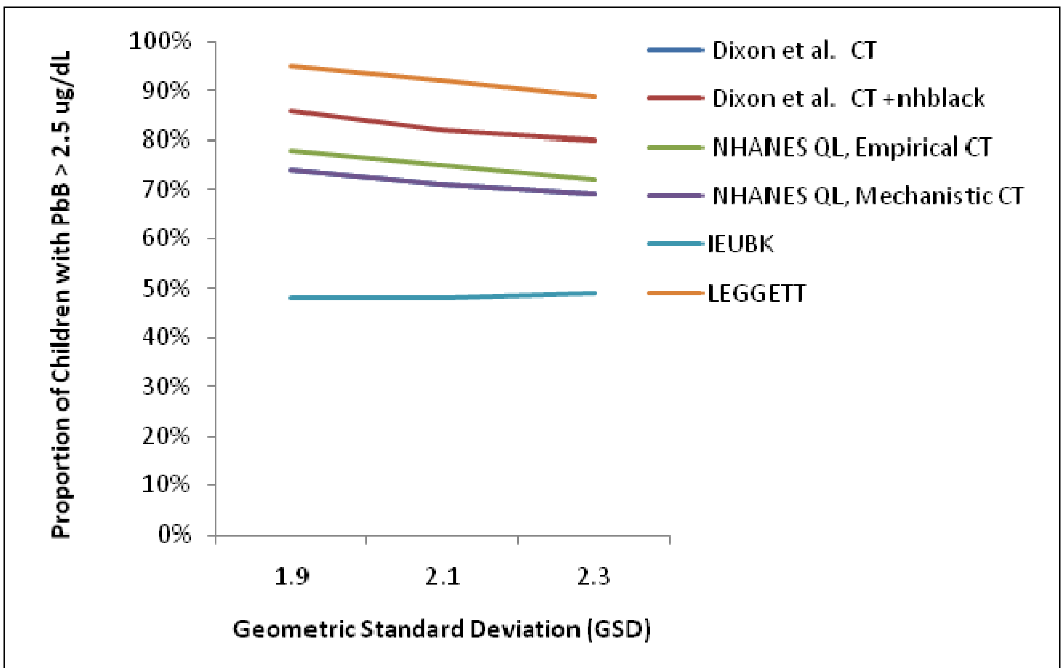


Figure 5-5. Predicted proportions of children with blood-lead concentrations > 2.5 µg/dL (floor dust loading 5 µg/ft^2)

6. Sensitivity Analysis of Model Predictions to Variations in Key Inputs

This section presents a brief discussion of most important assumptions and model inputs that affect the predictions of blood lead from the empirical (NHANES-based) and biokinetic models. As discussed in Section 1.1, in the absence of sufficient data to support meaningful probabilistic assessments (Monte Carlo analyses) of the uncertainty associated with blood-lead predictions, sensitivity analyses of selected variables were conducted.

6.1 Models Based on Empirical Data

As discussed in Section 3, two sets of empirical models were used to derive estimates of children's dust-lead levels: the original Dixon et al. (2009) regression and quasi-likelihood linearized models fit to the NHANES data using estimate dust lead concentrations as the exposure metrics. Because they are based on the same data set, these models have many characteristics in common and, not surprisingly, many of the same covariates were found to be significant predictors of children's blood-lead levels in the two sets of models.

Table 6-1 summarizes the factors that were included in the two sets of models and the specific variables that were retained. For each model, the magnitude of influence of significant covariates on predicted blood-lead concentrations was estimated, as shown in Table 6-1. The dependence of predicted blood lead on floor dust levels was described in Sections 3.2 and 3.3 for the two sets of models and summarized in Figure 5-1. As noted in Section 3, the specifications and exposure metrics differ between the Dixon et al. (2009) and the NHANES QL models. The former represents the influence of floor and window-sill dust as a log-log relationship to blood-lead concentration; the latter includes sill and floor dust as equivalent concentrations, in one case using empirically derived concentration conversion and in the other case using a mechanistic model to estimate dust concentrations from loading levels. As discussed in Section 3.3, the use of dust concentration metrics resulted in predicted blood-lead levels that provided reasonable fits to the observed data, especially in the case of the empirical model, which capture the curvilinearity of the relationship without the limitations of the log-log model.

Interestingly, at median floor dust and sill dust levels, the models derived using empirically derived and mechanistically derived dust concentrations predict the same blood-lead concentration that are within about 1 percent of one another, while the two models diverge substantially as dust loading increases (Figure 5-1). Note that the predictions based on the empirical (Dixon et al. and NHANES QL) models assume that the relative contributions of floor dust and sill dust lead will always be the same as that seen in the fitted regressions. The relative magnitudes of the coefficients for sill dust lead in the QL models confirm that the sill dust lead loading accounts for only a small proportion (less than 1 percent) of the total residential dust lead contribution to children's blood lead concentrations. This is despite the fact that typical sill dust lead loadings are much higher (about one order of magnitude or more) than floor dust loadings in the NHANES database.

Table 6-1. Influence of Dust Loading, Dust Concentration, and Other Covariates in the Dixon et al. (2009) and NHANES Quasi-Likelihood Regression Models for Children's Blood Lead

Factor	Variable(s) in Dixon et al. (2009) Regression	Effect on PbB Estimate at Median Dust Loading (compared to CT Scenario)	Variables in NHANES QL Model	Effect on PbB estimate at Median Dust Loading (Compared to CT Scenario, Empirical Scenario)
Floor dust loading	ln(floor) (only as interactions, see below)	See Figure 5-1	--	--
Window-sill dust loading	ln(window-sill)	~ 1% of floor dust	--	--
Floor dust concentration	--	--	Floor dust concentration (empirical), floor dust concentration (mechanistic)	1% difference between results based on mechanistic at median loadings, larger impact at higher loading (see Figure 5-1)
Window-sill dust concentration	--	--	Sill(empirical), Sill(mechanistic)	<1%
Age	Age, Age^2, Age^3, Age^4	See Figure 3-1	Age, Age^2, Age^3	See Figure 3-7
Ethnicity	non-Hispanic black (nHblack), other	32% (nHblack), 17% (other)	nHblack	29%
Birthplace	Mexico, elsewhere	14%	--	--
Income	PIR	−6% (doubling)	PIR	−6%(doubling)
Type of unit	Mobile home, small, large apartment	14% (mobile home), 7% (small), −12% (large apartment)	--	--
Date of construction	Post-1990, 1978–89, 1950–59, pre-1940 (1960–77 = baseline)	−2–3% (1978-post 1990), −3% (150-59), 19% (pre-1940)	Pre-1940	20% (pre-1940)
Household smoking	Smoker(s) present, cotinine	11% (smoker present), 4% (cotinine = 1 µg/dL)	Smoker(s) present	21%
Floor condition	Floor smooth and cleanable, interactions with ln(floor), $\ln(\text{floor})^2$, $\ln(\text{floor})^3$	14% (floor not smooth and cleanable)	Floor smooth and cleanable	−1%
Renovation/Repairs	Window replaced in pre-1978 house, interaction with ln(floor)	10%	--	--

Other covariates common to the two sets of models include representations of age, ethnicity, date of construction, presence or absence of smokers in the household, and flood condition. Some of the variables the models have in common exert similar effects on predicted blood-lead concentration; in both models, the polynomials exert a characteristic curvature on the predicted blood-lead concentrations, with maximum values predicted for children aged around 18–24 months. At median floor and dust lead loadings, both models predict blood-lead levels for non-Hispanic black children that are approximately 30 percent higher than for non-Hispanic whites, and both models predict a decrease of about 6 percent in blood-lead concentration when the ratio of family income is doubled from its median value of 1.1 to 2.2.

Both models also predict blood-lead levels in children living in houses built before 1940 that are approximately 20 percent higher than those predicted for the central tendency scenario, although the Dixon et al. model also predicts small effects (−2 to +3 percent) for children in houses built in other periods. The Dixon et al. model also predicts a smaller impact from having a smoker in the house (11 percent increase in blood lead) compared to the NHANES QL model (21 percent), and the Dixon et al. model also predicts a small dependence on measured serum continine levels.

6.2 Biokinetic Models

Because the biokinetic models predict very nearly linear relationships between lead intake and children's blood-lead concentrations (for a given age stratum), predicting the impact of changes on estimated blood-lead concentrations is relatively straightforward. Table 6-2 summarizes the proportions of total dust lead uptake (absorbed dose) contributed by the various sources under the baseline exposure scenario which provided intakes to both the IEUBK and Leggett models.

The first important feature of this model is the relatively large contributions to total lead dose from diet (38.6 percent) and drinking water (19.7 percent), for a total of 58.3 percent. Soil lead exposure under the baseline scenario accounts for 11.6 percent of total lead uptake, while inhalation exposures account for only a small proportion (1.1 percent.)

Lead exposures from dust exposures, both at home and away from home, together account for only an estimated 29.1 percent of total dust lead intake, with the contributions from at-home and away-from-home exposures being accounted for by the ratio of the estimated time spent in the two settings.

Local elasticities of the various model terms (the proportional change in lead uptake for a small proportional change in each variable) are shown in the last column of Table 6-2. For all the non-dust pathways that have simple multiplicative uptake models, the elasticity of each variable is approximately equal to the proportion of total lead uptake that is accounted for by the pathway. Thus, estimates of daily dietary lead intake and dietary absorption fractions have the largest elasticities among these pathways; a 1-percent change in these values would result in a 0.386-percent change in lead uptake, and for a very similar change in predicted blood-lead level for either biokinetic model.

Among the dust and soil pathway variables, the variable with the highest elasticity is the proportion of total dust exposure that is assumed to come from window-sill dust. A small change in this variable accounts for approximately an equal change in estimated blood-lead concentration (elasticity = −1.07), owing to the much higher assumed window-sill dust loading compared to floor dust. This elasticity, however, might overstate the importance of this variable in contributing to the total uncertainty in blood-lead estimates because the expected natural range of variation is probably only a few percent. Other variables that have relatively large elasticities (the amount of dust and soil ingested per day and the gastrointestinal absorption fraction for soil and dust) might be expected to contribute more to the total uncertainty in lead uptake estimates (and therefore in blood-lead estimates) owing to the expected high natural variability in these measures and the relatively small amount of data available to allow estimation of this variability. Among the dust concentration variables, residential floor dust concentration (and therefore loading), as expected, has the highest elasticity (0.213) because the model predicts that total dust exposure will be dominated by floor dust in the home. The elasticity of window-sill dust in the home is, as expected, approximately 0.01, while the estimated effect of floor and sill dust outside

Table 6-2. Baseline Lead Intake and Uptake Model[a] and Sensitivity to Changes in Intake Values

Variable/Quantity	Baseline Value	Proportion of Total Uptake	Local Elasticity (% change in PbB/ % change in variable)
Fraction of time spent in the home	0.77	--	−0.0001
Fraction of dust intake from floor	0.99	--	−1.067
Fraction of soil + dust intake which is soil	0.45	--	−0.126
Dust + soil ingestion (g/day)	0.11	--	0.403
Dust concentration, floor, home (mg/g)	34.4	--	0.213
Dust concentration, sill, home (mg/g)	166.8	--	0.010
Dust concentration, floor, outside the home (mg/g)	34.4	--	0.064
Dust concentration, sill, outside the home (mg/g)	166.8	--	0.001
Dust absorption fraction	0.5	--	0.287
Lead uptake from home dust (mg/day)	0.83	22.3%	--
Lead Uptake from dust out of home (mg/day)	0.25	6.7%	--
Lead Uptake from all dust (mg/day)	1.08	29.1%	--
Soil concentration, home (mg/g)	29	--	0.085
Soil concentration, outside the home (mg/g)	29	--	0.023
Soil absorption fraction	0.3	--	0.112
Lead Uptake from home soil (mg/day)	0.33	8.9%	--
Lead Uptake from out of home soil (mg/day)	0.10	2.7%	--
Lead Uptake from all soil (mg/day)	0.43	11.6%	--
Dietary absorption fraction	0.5	--	0.386
Dietary lead intake (mg/day)	2.87	--	0.386
Lead Uptake from diet (mg/day)	1.44	38.6%	--
Water lead concentration (mg/L)	4.61	--	0.197
Water absorption fraction	0.5	--	0.197
Water consumption (L/day)	0.317	--	0.197
Lead uptake from water (mg/day)	0.73	19.7%	--
Total ingestion lead uptake (mg/day)	3.68	98.9%	--
Air concentration (mg/m^3)	0.01	--	0.011
Ventilation rate (m3/day)	9.5	--	0.011
Lung absorption fraction (unitless)	0.42	--	0.011

Uptake from air (mg/day)	0.040	1.1%	--
Total Lead Uptake, All Pathways, Sources (mg/day)	3.72	100.0%	--

[a] Model intakes for children aged 2–3, proportional contributions based on median floor (0.55 µg/ft^2) and window-sill (6.0 µg/ft^2) dust loading from NHANES data, soil concentration = 29 mg/kg; sources for exposure factor values are presented in Table 2-3.

Table 6-2 cont. Baseline Lead Intake and Uptake Model[a] and Sensitivity to Changes in Intake Values

the home are correspondingly less, owing to the relatively small proportion of time spent in these locations, compared to the time spent at home.

Although these local elasticities provide a good first approximation of the sensitivity of blood-lead predictions to the various biokinetic model inputs, the overall effect of variations in multiple input terms could be quite different. For example, the influence of window-sill dust and soil and dust exposures outside the home are predicted to be small in the vicinity of the baseline parameter set because, under these assumptions, the proportion of dust exposure attributed to dust and the contribution of out-of-home exposure to both sill and dust are set to low values. If these estimates change, then the sensitivity of blood lead to sill dust and out-of-home exposures could be increased.

7. Summary

7.1 Approaches for Estimating Blood-lead Concentrations Associated with Candidate Hazard Standards

Approaches have been derived for predicting how the candidate residential dust lead hazard standards may affect children's blood-lead levels. These involve (1) application of the 1999–2004 NHANES data on residential dust levels to develop empirical models for predicting blood-lead levels, and (2) use of sensitivity analyses on key variables to evaluate how changes in input variables and assumptions affect predictions from both empirical and biokinetic models. The abbreviated examination was necessitated by the lack of sufficient data to support meaningful probabilistic analyses. Nonetheless, some comparisons were possible with biokinetic model outcomes to examine how observed data compare to theory.

The NHANES data, which include dust loading and blood-lead measurements and multiple covariates for more than 2,000 children, provide a unique new resource permitting the derivation of empirical dust lead-blood lead models. In this report, both published regression models (Dixon et al. 2009) and newly developed quasi-likelihood regressions were examined to investigate the relationships between residential floor and window-sill loading. These models have provided useful insights on the relationships between dust lead, age, ethnicity, income, and housing age and condition on children's blood-lead levels. In particular, both the published models and the reanalysis of the NHANES data display a relatively small influence of window-sill dust loading on blood lead, providing support for a key input when biokinetic models are used. Also, the empirical models confirm non-Hispanic black children as a key sensitive population, with significantly higher predicted blood-lead concentrations, even when other demographic and economic variables have been controlled.

7.2 Proportions of Children Predicted to Have Blood-lead Concentrations above Target Levels

The potential impacts of candidate floor and sill dust standards were assessed in terms of the proportions of children predicted to have blood-lead concentrations – in the year when they would be most sensitive to lead exposure – above target levels of 5, 2.5, and 1 μg/dL. These levels are quite stringent, and were chosen because recent epidemiological data reveal increasing evidence of adverse effects on children's neurological development at low blood-lead concentrations. As shown in Table 5-1, part B, the geometric mean blood-lead levels in U.S. children in recent years have ranged from about 2.3 to 1.5 μg /dL. Thus, even in the absence of significant levels of dust exposure, a substantial proportion (more than 50 percent) of young children would be expected to have blood-lead concentrations exceeding 1 μg/dL, and smaller but not insignificant proportions would be expected to exceed the other target levels as well.

The results of the analyses presented in Section 5 and Appendix D confirm that, under reasonable input assumptions (CT or "baseline"), both the empirical and biokinetic models predict that large proportions (17–99 percent) of young children would have blood-lead levels above all three target levels, even if the standards were set at loading levels far less than the current values (40 μg/ft^2 for floor dust and 250 μg/ft^2 for window-sill dust). This general finding is robust across reasonable ranges of model inputs and exposure factor assumptions.

7.3 Major Sources of Uncertainty in Blood-lead Estimates

The general agreement among the CT and baseline empirical and biokinetic models strongly supports the overall findings related to blood-lead impacts described in the previous sections. The blood-lead predictions from both the empirical models, however, are subject to several sources of considerable uncertainty.

With regard to the empirical models, although the NHANES data represent a unique resource that can support the development of dust lead-blood lead models, the data are not without their limitations. First, relatively few data points for high floor dust loading are available, with more than 98 percent of the data falling below 5 $\mu g/ft^2$. Thus, the few data points that are present for high exposures are extremely influential in determining the goodness of fit of any statistical model (even log-log). As noted in Section 3.3, the best fitting log-log model of these data predicts supra-linearity at low exposures and decreasing blood-lead levels with exposure at high dust levels. Fitting a rather complex quasi-likelihood model to the data was therefore chosen, as was constraining the coefficients for floor and sill dust to be linear, so that a model could be obtained that is consistent with linear low-dose biokinetics and does not predict decreasing blood leads at higher dust exposures. The best fit was obtained by using a model that takes estimated dust concentration, rather than loading, as inputs, so that the uncertainty associated with dust loading-dust concentration relationships is added to the inherent statistical uncertainty associated with model fitting. Notably, however, the empirical dust concentration model was found to afford a good fit to the data, consistent with the observed curvilinearity of the dust lead-blood lead relationship, but without the undesirable side effects of the log-log model.

The potential sources of uncertainty and their impacts on blood-lead predictions from the biokinetic models are discussed in Section 6.2. As noted there, although the IEUBK and Leggett models require numerous inputs (e.g., environmental concentrations, absorption fractions, behavioral data, dietary and drinking-water lead intakes), relatively few of the dust-related variables were found to have a large impact (at least locally) on predicted blood-lead levels. Among the exposure-related variables having the largest impact on predicted blood-lead levels, the fraction of exposure attributed to window-sill dust had the largest effect (elasticity = 1.07) on blood-lead predictions. As discussed above, however, the likely range of variability in this term (which was assigned a baseline value of 0.01 on the basis of floor-sill relative areas) is rather small, and the empirical (NHANES) models support the conclusion that sill dust influence on children's blood lead is quite small.

Most of the variables characterizing exposures outside the home (e.g., in child-occupied facilities or public and commercial buildings) had relatively little impact on estimated blood-lead impacts of residential sill dust. As pointed out in Section 6.2, this finding is a result of the assumptions made for the baseline scenario – that the proportions of time children would spend in these microenvironments would be quite small. Although this assumption is reasonable for the most sensitive children (aged 1–2 years), the existence in this age range of a subpopulation that spends more time outside the home and thus might be more sensitive to exposures in other microenvironments cannot be ruled out.

The sensitivity analysis described in Section 6.2 is limited to variables that affect lead exposures and uptake; it does not address intrinsic uncertainties in the biokinetic models and their terms. Some of this uncertainty was addressed by investigating how the impacts of the range of blood-lead geometric standard deviation values (1.9, a central tendency value of 2.1, and 2.3) influence the projected proportions of children having blood-lead concentrations above various target levels. Although varying the blood-lead geometric standard deviation had only modest effects, the variation in blood-lead geometric standard deviation incorporates contributions from both variability in exposures factors and biokinetic parameters. Neither the IEUBK model nor Leggett model incorporates variables that the empirical models show to be important (ethnicity, income), nor do they enable analysis of the impacts of genetic variations (in, for example δ-aminolevulinic acid dehydratase genotype) that are known significantly to affect lead binding in red blood cells and bone deposition.

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Appendix A

Summary of Floor Dust-Sill Dust Lead Loading Imputation Regression

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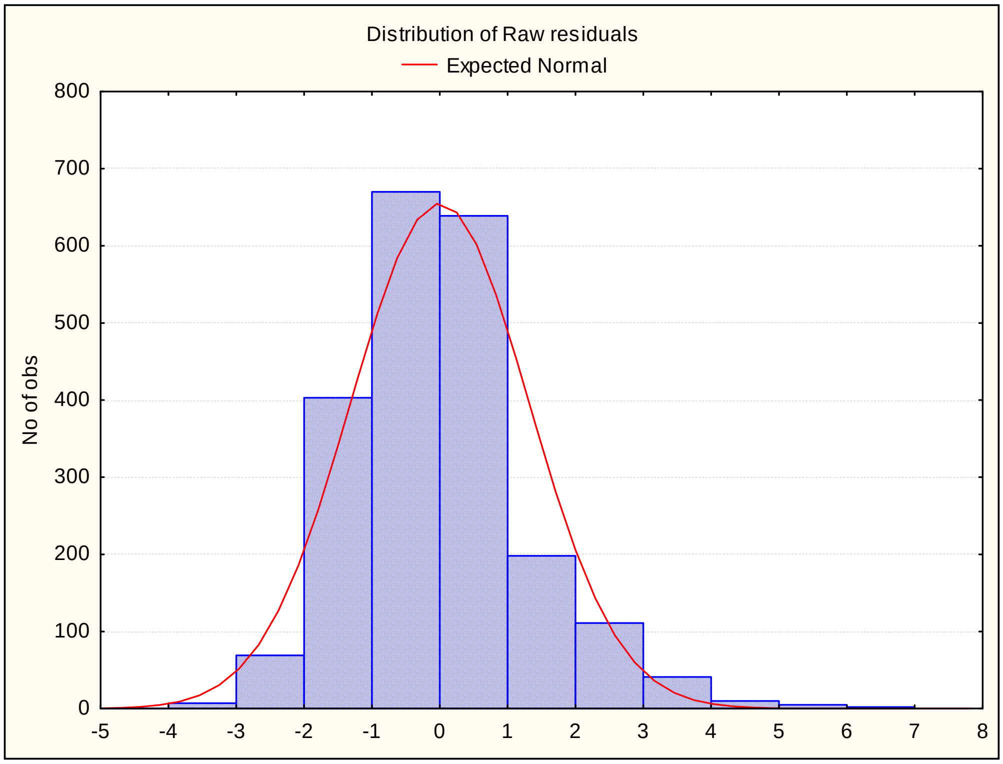
APPENDIX A.
Summary of Floor Dust-Sill Dust Lead Loading Imputation Regression

Output from Statistica® Multiple Regression Module

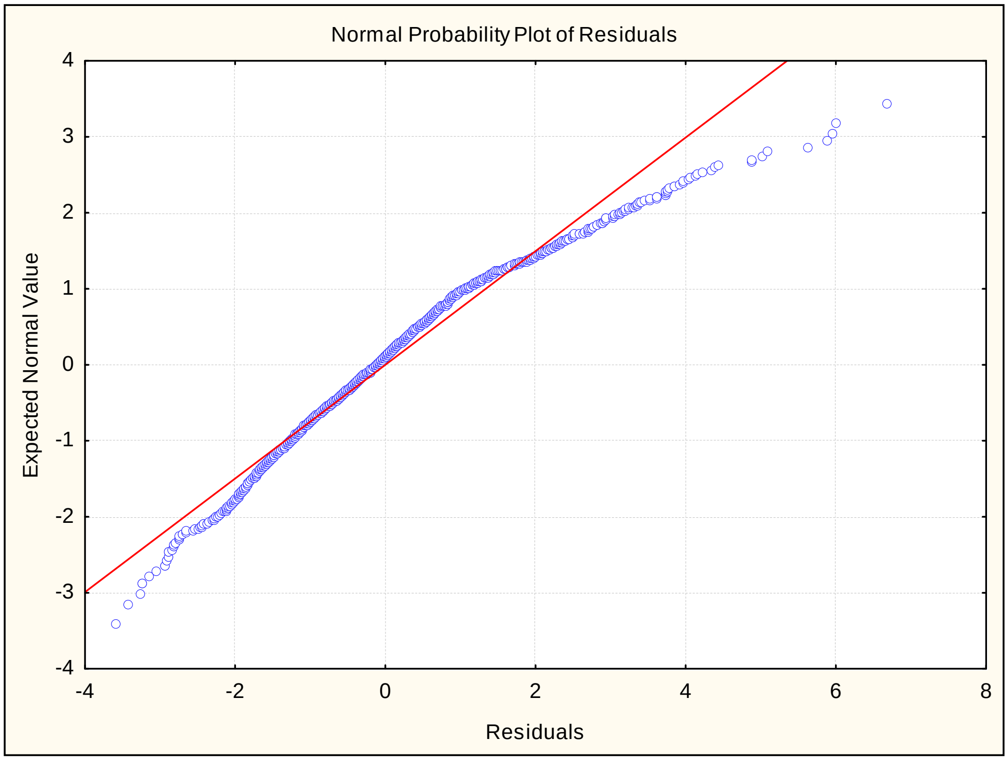
Unweighted regression using NHANES data floor dust vs. window-sill dust loading with covariates.

	Beta	Std.Err. of Beta	B	Std.Err. of B	t(990)	p-level
Intercept			1.615822	0.134840	11.98323	0.000000
YR2	-0.053823	0.027655	-0.194343	0.099854	-1.94628	0.051904
nhblack	0.080693	0.029135	0.326644	0.117940	2.76958	0.005718
sillnotsmooth	0.117193	0.028266	0.707492	0.170641	4.14609	0.000037
rmdirty	0.071448	0.027838	0.353510	0.137734	2.56662	0.010415
lncombfloor	0.266525	0.031282	0.375604	0.044085	8.51996	0.000000
trailer	0.059966	0.029581	0.351297	0.173295	2.02717	0.042913
apartmnt	-0.056839	0.028418	-0.258018	0.129000	-2.00015	0.045757
blt78_89	0.080296	0.034816	0.346786	0.150367	2.30627	0.021302
blt60-77	0.122657	0.036437	0.492046	0.146170	3.36627	0.000791
blt50_59	0.169759	0.034130	0.853226	0.171543	4.97385	0.000001
blt40_49	0.145453	0.031705	1.034092	0.225408	4.58766	0.000005
bltpre40	0.316108	0.037550	1.421678	0.168878	8.41839	0.000000

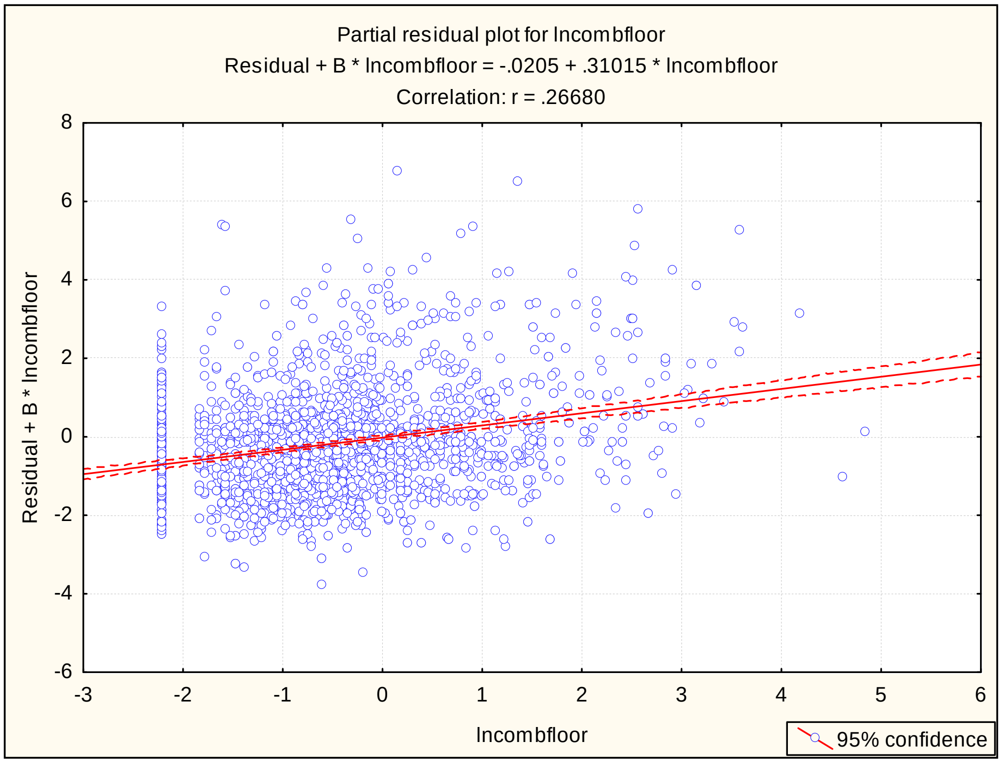
The following charts illustrate the regression diagnostics (residual patterns for the floor-dust-window-sill dust regression (above). (In these figures, log(·) indicates the natural logarithm.)

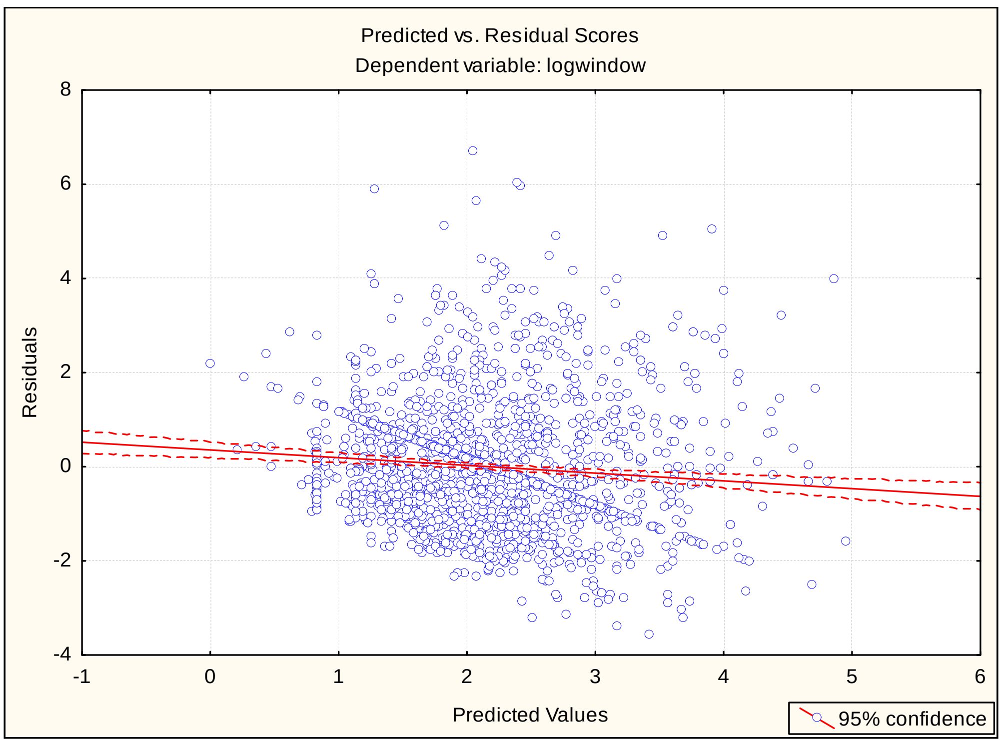


Distribution of Raw residuals
Expected Normal
No of obs
800
700
600
500
400
300
200
100
0
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
8

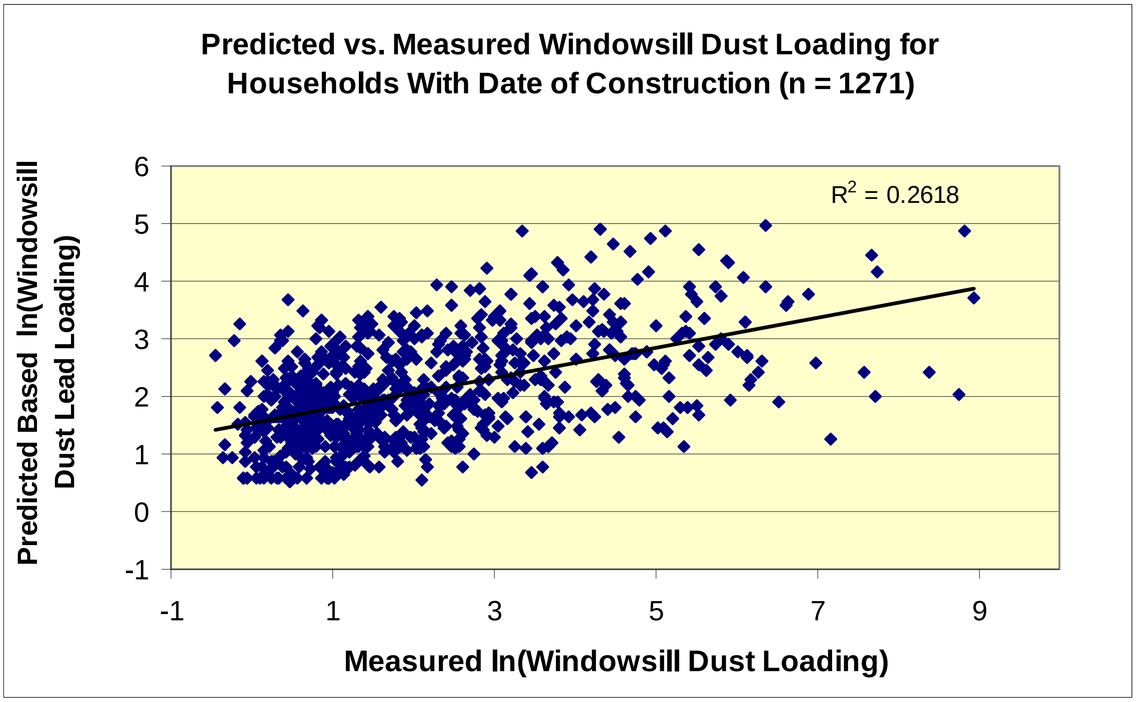


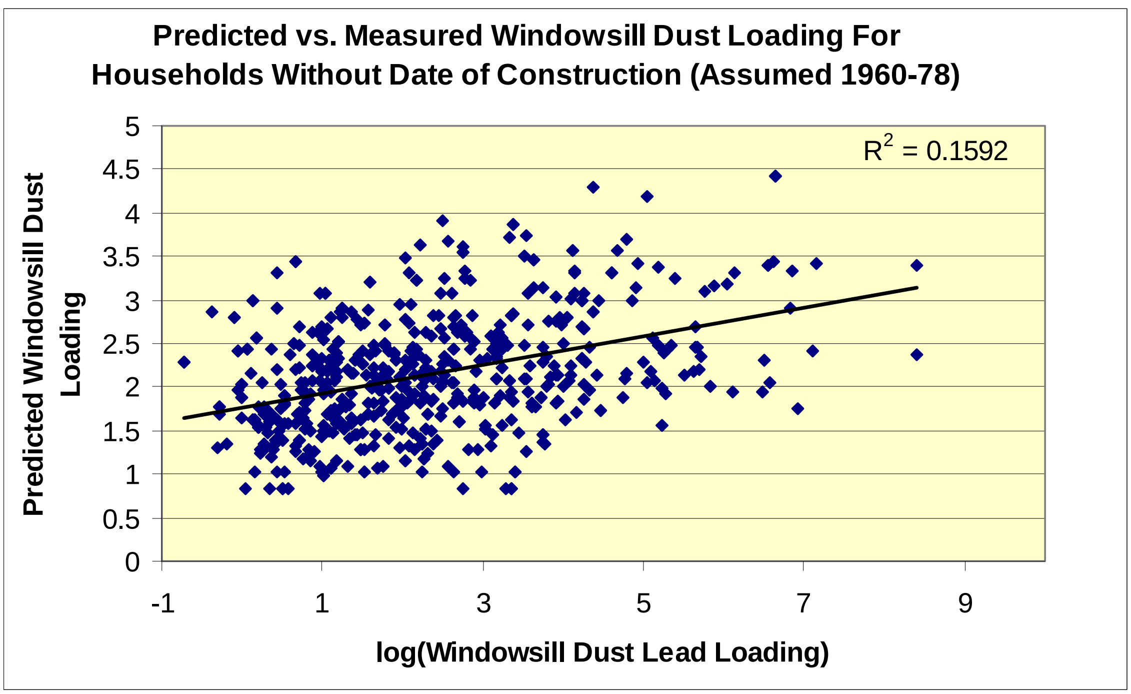
Normal Probability Plot of Residuals
Expected Normal Value
4
3
2
1
0
-1
-2
-3
-4
-4
-2
0
2
4
6
8
Residuals

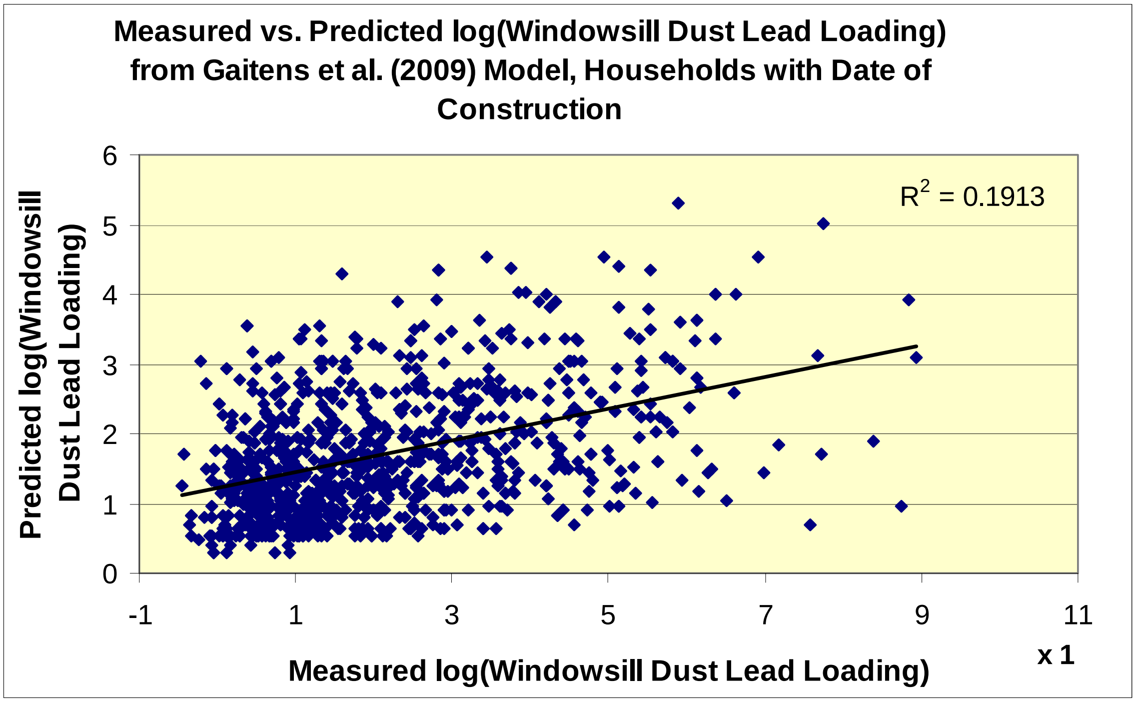

Partial residual plot for lncombfloor
Residual + B * lncombfloor = -.0205 + .31015 * lncombfloor
Correlation: r = .26680
Residual + B * lncombfloor
lncombfloor
95% confidence
8
6
4
2
0
-2
-4
-6
-3
-2
-1
0
1
2
3
4
5
6

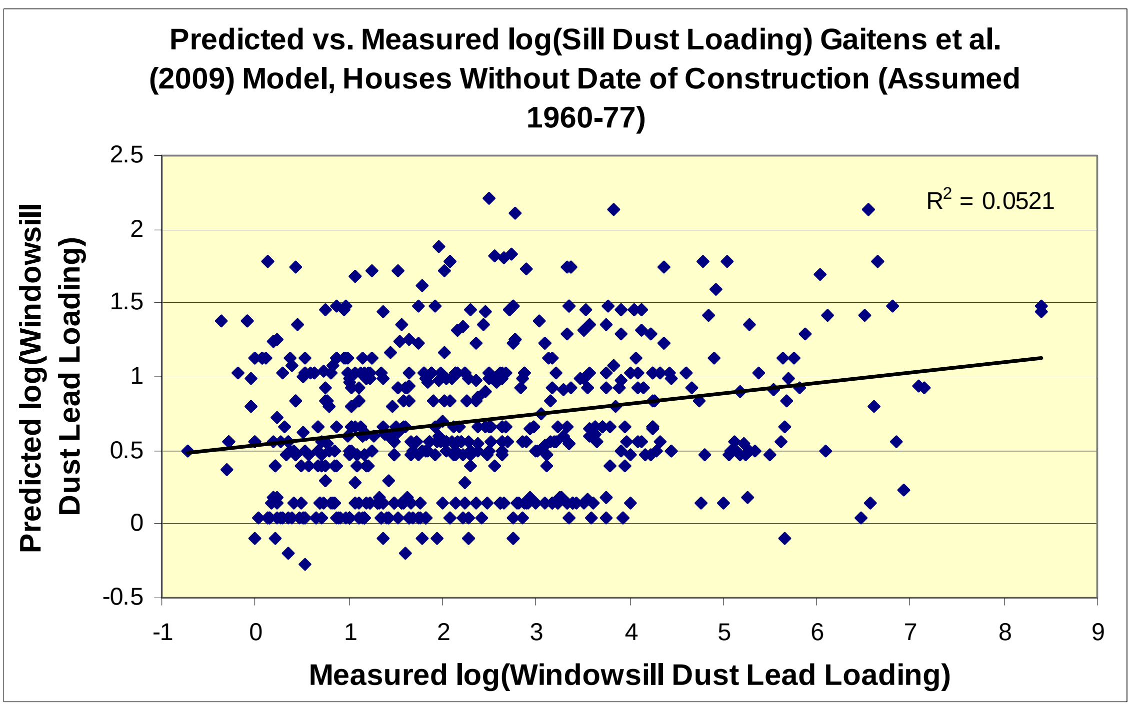

Predicted vs. Residual Scores
Dependent variable: logwindow
Residuals
Predicted Values
95% confidence
8
6
4
2
0
-2
-4
-1
0
1
2
3
4
5
6

The following four charts compare the sill dust values imputed using the floor dust-sill dust regression model with the imputed values from the Gaitens et al. (2009) model, which does not include floor dust lead loading.






Measured vs. Predicted log(Windowsill Dust Lead Loading) from Gaitens et al. (2009) Model, Households with Date of Construction
R^2 = 0.1913
Predicted log(Windowsill Dust Lead Loading)
Measured log(Windowsill Dust Lead Loading)
x 1
6
5
4
3
2
1
0
-1
1
3
5
7
9
11


Predicted vs. Measured log(Sill Dust Loading) Gaitens et al. (2009) Model, Houses Without Date of Construction (Assumed 1960-77)
R^2 = 0.0521
Predicted log(Windowsill Dust Lead Loading)
Measured log(Windowsill Dust Lead Loading)
2.5
2
1.5
1
0.5
0
-0.5
-1
0
1
2
3
4
5
6
7
8
9

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Appendix B

Quasi-likelihood Generalized Linear Model for Children's Blood Lead

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Appendix B.
Quasi-likelihood Generalized Linear Model for Children's Blood Lead Based on 1999-2004 Data.

In order to address the issues associated with the complex stratification and clustering methods used in the NHANES, the *survey* package (Lumley 2010) of the R statistical computing system was used to estimate the regression models. As discussed in Section 3.3, Generalized Linear Models were estimated which included estimated dust lead concentrations and covariates as described below. Data were imported into R in comma-delimited (.csv) format. The survey package requires that the survey design be specified; the following specification was used:

> *Desgn <- svydesign(id= ~SDMVPSU,strata= ~SDMVSTRA, weights= ~WTMEC, data= nhm, nest = TRUE)*

Where SDMVPSU and SDMVPSTRA are the NHANES Masked Variance Pseudo-PSU and Masked Variance Pseudo-Stratum, respectively and the WTMEC variable contained the sample weights.

Regression were fit to dust lead concentrations that were estimated either using the exponential "empirical" model or the linear "mechanistic" model, as described in Section 3.3.3. To preserve consistency with linear low-dose steady-state biokinetics, concentration terms were constrained to enter the model only in linear form (not as powers or logs) and in linear combinations with other covariates. Transformations of other variables (age) were tested for significance and predictive power, however.

The quasi-likelihood model was fit by manual stepwise addition and subtraction, with decisions regarding variable inclusion or removal made based on statistical significance (nominal $p < 0.05$) or marginal deviance reduction. Linear terms and simple transformations were tested first, followed by interaction terms, and then selected variables were removed one at a time. The order of inclusion and removal was also informed by exploratory data analysis (strength of simple correlations). Table B-1 shows the order of addition and removal of variables and Table B-2 provides variable definitions.

Table B-1. Order of Stepwise Addition and Removal of Variables from Quasi-Likelihood Model for Children's Blood Lead

Regression Number	Null Deviance	Residual Deviance	Deviance Reduction	Variables added/retained in Step	Variables Eliminated in Step
Forward Addition					
r6	2512	1767	0.297	nhblack, age, age2, age3	floorsm
r7	2512	1675	0.333	INDFMPIR	bornus, bornmex
r8	2512	1662	0.338	bltpre40	bornothr
r9	2512	1657	0.340	--	blt40-49, blt50-59, blt60-78
r10	2512	1659	0.340	--	blt79-90, X1990post, owned, rented
r11	2512	1658	0.340	--	trailer, apartment, detached
r12	2512	1629	0.352	chipinside, smoke	--
r13	2512	1613	0.358	floorsm*floorconc	--
r14	2512	1598	0.364	floorconc*age	--
r15	2512	1597	0.364		floorconc*age2, floorconc*age3
r16	2512	1592	0.366	nhblack*INDFMPIR	smoke*floorconc
r17	2512	1594	0.365	--	chipinside*floorconc

Table B-1. Order of Stepwise Addition and Removal of Variables from Quasi-Likelihood Model for Children's Blood Lead

Regression Number	Null Deviance	Residual Deviance	Deviance Reduction	Variables added/retained in Step	Variables Eliminated in Step
r18	2512	1592	0.366	--	floorconc*bltpre40
r19	2512	1589	0.367	--	chipinside*bltpre41
r20	2512	1594	0.365	--	--
Backwards Removal (from r20)					
r21	2512	1598	0.364	--	r20- nhblack*INDFMPIR
r22	2512	1603	0.362	--	r21-floorsm
r23	2512	1605	0.361	--	r22+floorsm-chipinside
r24	2512	1618	0.356	--	r23-floorsm
r25	2512	1623	0.354	--	r24 + floorsm - bltpre40
r26	2512	1605	0.361	--	r25 + bltpre40

Table B-2. Variables Names, Sources, Definitions

Variable Name	NHANES Variable	Definition
SEQN	SEQN	Respondent sequence number
age	RIDAGEMN	Age (months)
age2		Age (months)^2
age3		Age (months)^3
age4		Age (months)^4
mex	RIDRETH1	RIDRETH1 = 1, Mexican American
hisp		RIDRETH1 = 2, Other Hispanic
nhwhite		RIDRETH1 = 3, Non-Hispanic White
nhblack		RIDRETH1 = 4, Non-Hispanic Black
othereth		RIDRETH1 = 5, Ethinicity Other
bornus	DMDBORN	DMDBORN = 1 Born in U.S.
bornmex		DMDBORN = 2 Born in Mexico
bornothr		DMDBORN = 3 Born in other country
INDFMPIR	INDFMPIR	Family income relative to poverty level
pbb	LBXBPB	Index child blood lead, µg/dL
sillsm	DCQ250	DCQ250 = 1, Window sill smooth and cleanable
sillnot		DCQ250 = 2, Window sill not smooth and cleanable
floorsm	DCQ160	DCQ160 = 1, Floor smooth and cleanable
floornot		DCQ160 = 2, Floor not smooth and cleanable
rmdirty	DCQ400	DCQ400 = 1, Sampled room dirty

Table B-2.cont. Variables Names, Sources, Definitions

floorconc	LBXDFS, LBXDFSF	Floor dust lead concentration, µg/g, calculated using empirical dust regression
floorconc2		Floor dust concentration (empirical)^2
floorconc3		Floor dust concentration (empirical)^3
floormech		Floor dust lead concentration, µg/g, calculated using mechanistic model
floormech2		Floor dust concentration (mechanistic)^2
floormech3		Floor dust concentration (mechanistic)^3
windconc	LBDDWS	Window-sill dust lead concentration, µg/g, calculated using empirical dust regression
windconc2		Window-sill dust concentration (empirical)^2
windconc3		Window-sill dust concentration (empirical)^3
windmech		Window-sill dust lead concentration, µg/g, calculated using mechanistic model
windmech2		Window-sill dust concentration (mechanistic)^2
windmech3		Window-sill dust concentration (mechanistic)^3
sillimp		Window-sill dust concentration imputed (0-1)
trailer	HOD010	HOD010 = 1, Unit type = mobile home
detached		HOD010 = 2, Unit type = Detached house
attached		HOD010 = 3, Unit type = Attached house
apartmnt		HOD010 = 4, Unit type = Apartment
othertype		HOD010 = 5, Unit type = Other
dorm		HOD010 = 6, Unit type = Detached
smallapt	HOD030	HOD30 = 1-4 (less than 10 apartments in building)
bigapt		HOD30 = 5-7 (10 or more apartments in building)
x1990post	HOD040	HOD040 = 1 date of construction = post-1990
blt78_89		HOD040 = 2 date of construction = 1978-1989
blt60-77		HOD040 = 3 date of construction = 1960-1977
blt50_59		HOD040 = 4 date of construction = 1950-1959
blt40_49		HOD040 = 5 date of construction = 1940-1949
bltpre40		HOD040 = 6 date of construction = pre-1940
bltpre78		HOD040 = 3-6, date of construction = pre-1978
bltpre50		HOD040 = 5 or 6, date of construction = pre-1950
owned	HOQ065	HOQ065 = 1, home owned
rented		HOQ065 = 2, home rented
other		HOQ065 = 3, home other
chipinside	HOD160	HOD160 = 1, indoor paint peeling, flaking or chipping
bigchipinside	HOD170	HOD170 = 1, Area of peeling indoor paint greater than 22x26 in.
chipout	HOD190	HOD190 = 1, Outside paint peeling, flaking, or chipping

Table B-2.cont. Variables Names, Sources, Definitions

bigchipout	HOD210	HOD210 = 1, Area of outside paint chipping bigger than door
paint	HOD140	HOD140 = 1, home painted in last 12 months
scrape	HOD150	HOD150 = 1, old paint scraped when home was painted
renov	HOD220	HOD220 = 1, window, cabinet or wall renovation
smoke	SMD410	SMD410 = 1, one or more smokers present in the home
WTMEC	WTMEC2YR	6-Year MEC Exam Weight (calculated from 2-year weights)
WTINT	WTINT2YR	6-Year Interview Weight (calculated from 2-year weights)
SDMVPSU	SDMVPSU	Masked Variance Pseudo-PSU
SDMVSTRA	SDMVSTRA	Masked Variance Pseudo-Stratum

The 64 variables shown in Table B-2 represent those considered in performing the reanalysis. Where the NHANES variable has multiple categories (e.g., RIDRETH1), each line represents a (0,1) variable in the reanalysis. Thus, the variable nhblack was 1 if the respondent described him/herself as non-Hispanic and Black and 0 otherwise; this corresponds to RIDRETH1=4.

The regression "r26" appeared to provide the best compromise between the amount of deviance explained, significance of variables, and parsimony. The R summary for the model was:

Call:

```
svyglm(pbb ~ floorconc + windconc + nhblack + age + age2 + age3 +
   INDFMPIR + bltpre40 + smoke + floorsm * floorconc + floorconc *
   age, desgn, family = quasi(link = "identity", variance = "mu"))
```

Survey design:

```
svydesign(id = ~SDMVPSU, strata = ~SDMVSTRA, weights = ~WTMEC,
   data = nhm, nest = TRUE)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	4.134e-01	5.246e-01	0.788	0.43646
floorconc	2.696e-02	3.870e-03	6.968	6.80e-08 ***
windconc	2.187e-04	9.341e-05	2.341	0.02560 *
nhblack	6.974e-01	1.252e-01	5.570	3.78e-06 ***
age	1.432e-01	5.715e-02	2.506	0.01748 *
age2	-4.579e-03	1.713e-03	-2.673	0.01172 *
age3	4.266e-05	1.546e-05	2.759	0.00951 **
INDFMPIR	-1.587e-01	2.572e-02	-6.171	6.63e-07 ***
bltpre40	4.927e-01	1.882e-01	2.618	0.01340 *
smoke	5.040e-01	1.493e-01	3.375	0.00195 **
floorsm	2.743e-01	1.614e-01	1.700	0.09890 .
floorconc:floorsm	-7.130e-03	2.749e-03	-2.594	0.01421 *
floorconc:age	-2.651e-04	7.962e-05	-3.329	0.00220 **

Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

The following figures show the regression residuals and the predicted blood lead concentrations as a function of floor dust and window-sill dust loading (dust concentrations used to fit the model were derived based on the empirical loading-concentration model.) The large variance of the predicted and observed variables are evidence, along with the much stronger correlation between predicted blood lead and floor lead than between predicted values and window-sill lead.

Figure B-1. Residuals from q-likelihood Linear Model Fit to Dust Concentrations (Empirical Model)

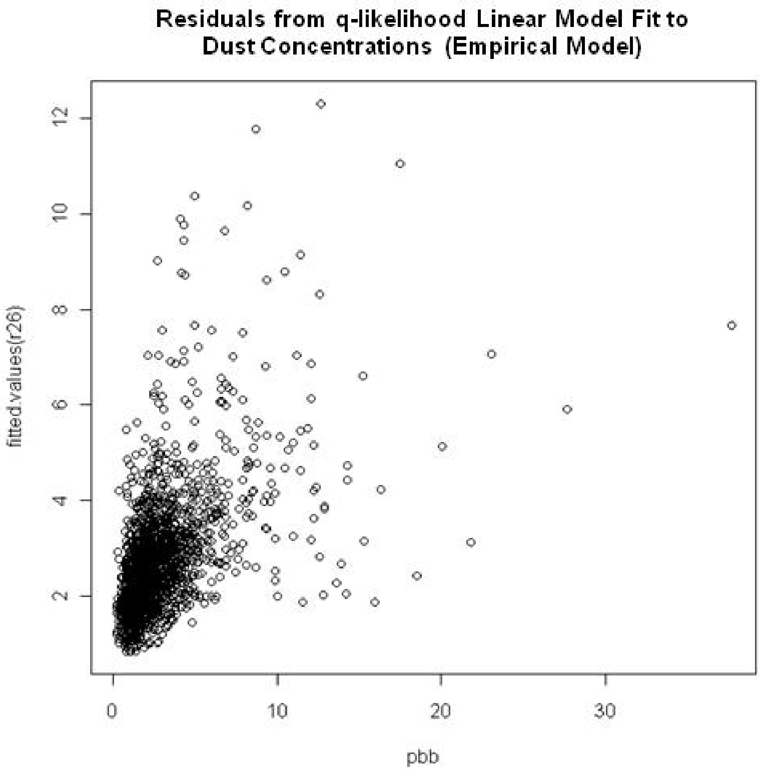


Figure B-2. Predicted PbB versus Floor Dust Pb Concentrations (Empirical Model)

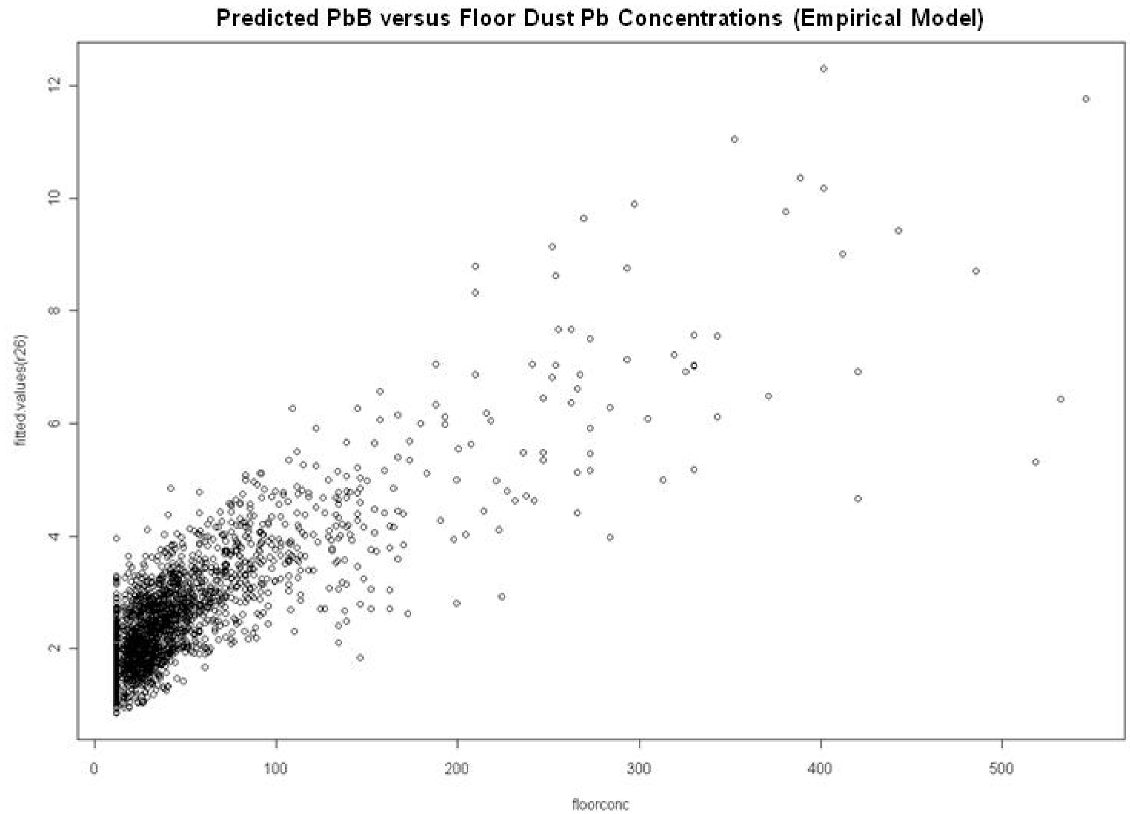
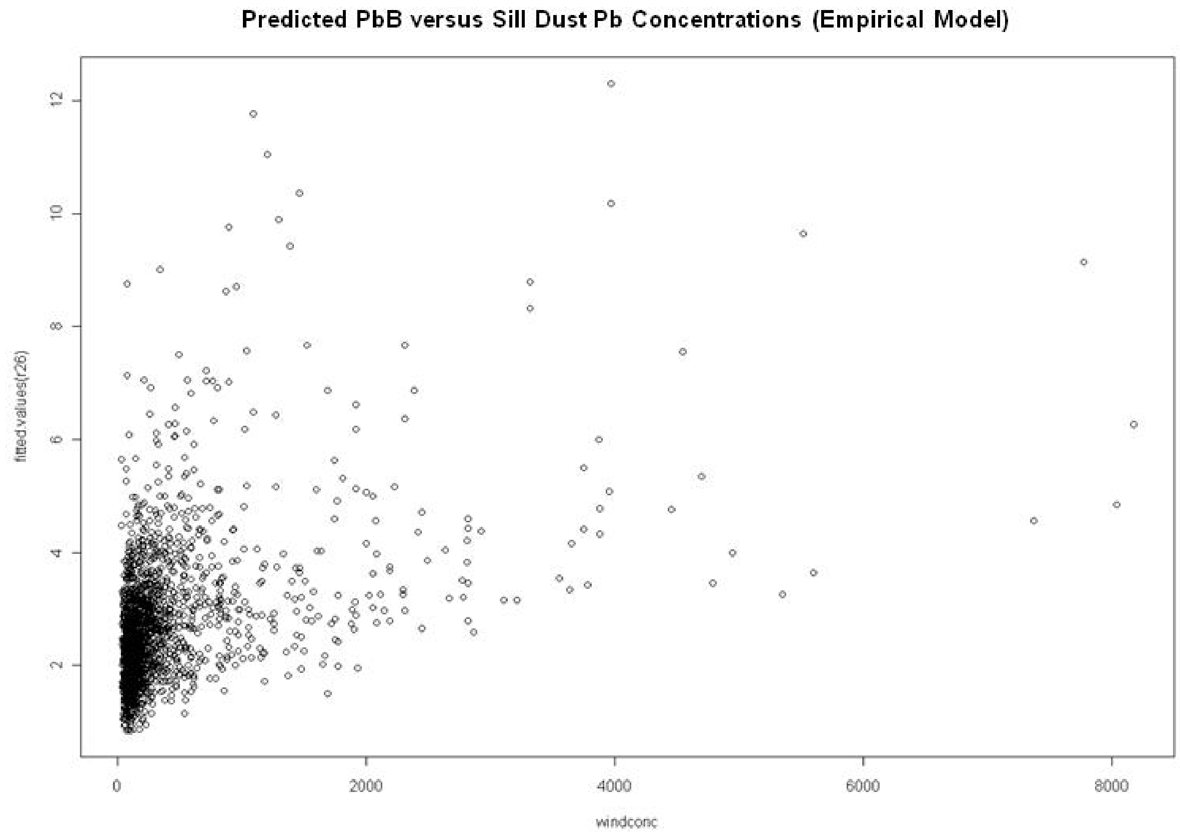


Figure B-3. Predicted PbB versus Sill Dust Pb Concentrations (Empirical Model)



The best fitting regression based in dust concentrations derived using the mechanistic model is “rm1”:

Call:
svyglm(pbb ~ floormech + windmech + nhblack + age + age2 + age3 +
INDFMPIR + bltpre40 + smoke + floorsm * floormech + floormech *
age, desgn, family = quasi(link = "identity", variance = "mu"))

Survey design:
svydesign(id = ~SDMVPSU, strata = ~SDMVSTRA, weights = ~WTMEC,
data = nhm, nest = TRUE)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	8.464e-01	5.234e-01	1.617	0.115674
floormech	2.347e-02	3.825e-03	6.136	7.32e-07 ***
windmech	3.433e-05	1.411e-05	2.434	0.020697 *
nhblack	7.878e-01	1.352e-01	5.827	1.79e-06 ***
age	1.491e-01	5.679e-02	2.625	0.013167 *
age2	-4.880e-03	1.698e-03	-2.874	0.007145 **
age3	4.546e-05	1.536e-05	2.960	0.005747 **
INDFMPIR	-1.763e-01	2.683e-02	-6.573	2.09e-07 ***
bltpre40	6.577e-01	2.124e-01	3.096	0.004057 **
smoke	5.614e-01	1.519e-01	3.695	0.000818 ***
floorsm	2.367e-01	1.351e-01	1.753	0.089253 .
floormech:floorsm	-7.15e-03	2.374e-03	-3.012	0.005042 **
floormech:age	-2.571e-04	7.763e-05	-3.312	0.002306 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The following figures show the regression residuals and the predicted blood lead concentrations as for the previous regression.

Figure B-4. Residuals from q-likelihood Linear Model Fit to Dust Concentrations (Empirical Model)

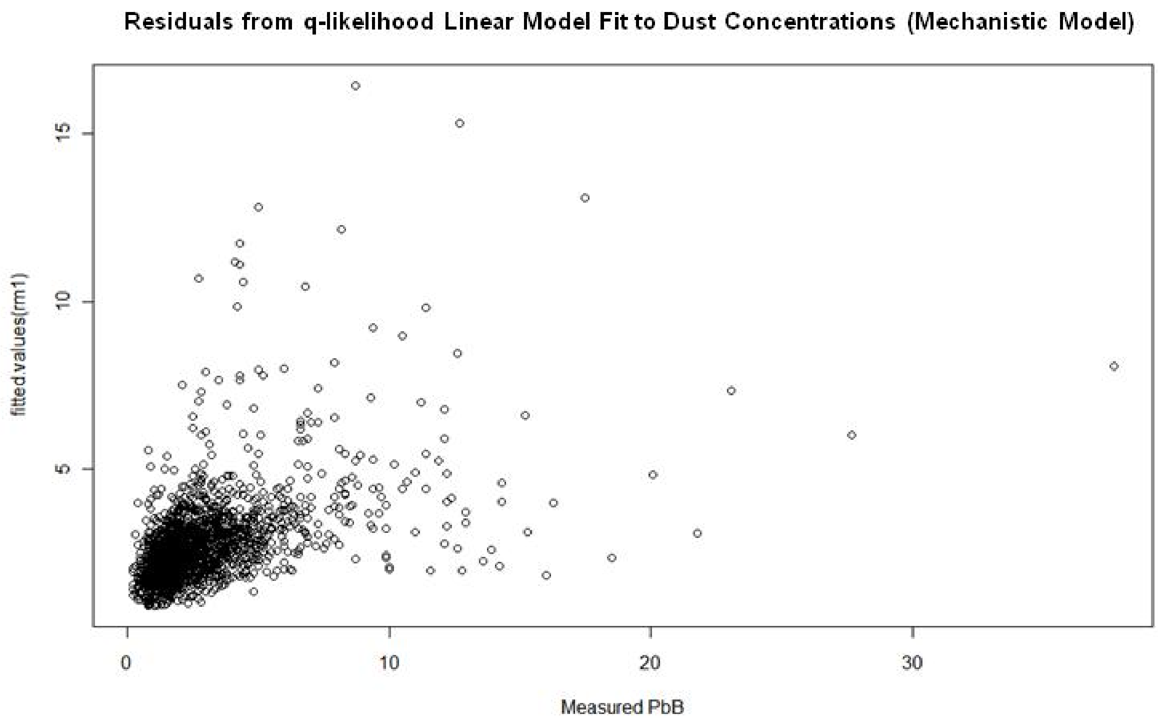


Figure B-5. Predicted PbB versus Floor Dust Pb Concentrations (Mechanistic Model)

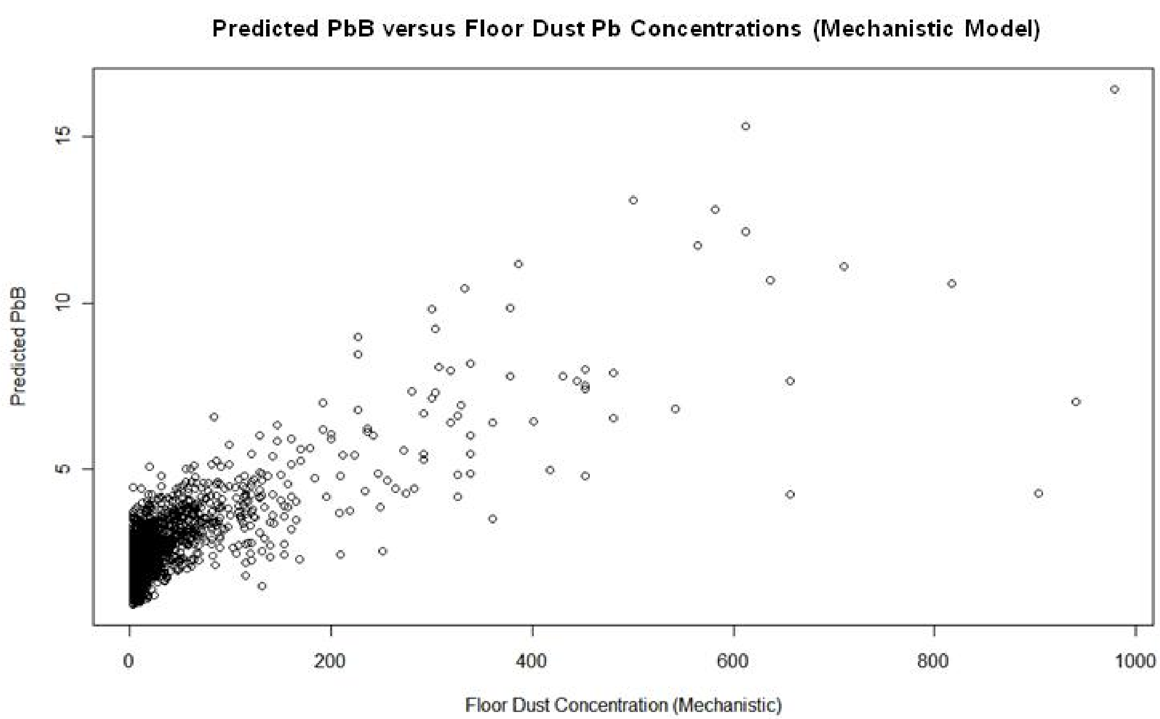
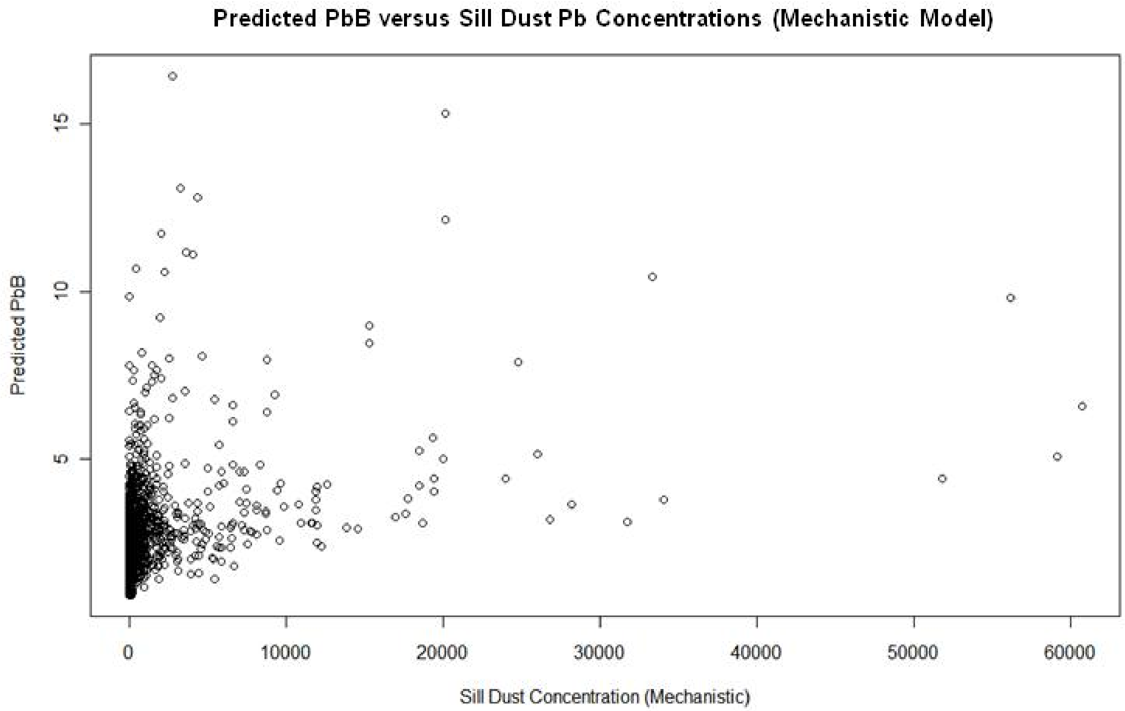


Figure B-6. Predicted PbB versus Sill Dust Pb Concentrations (Mechanistic Model)



Appendix C

Batch Mode Shell Input Page for Leggett Model

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Appendix C. Leggett Model Batch Mode Operating Shell Input Page

Leggett I/O Processor
Last modified 9/10/10

Instructions:

Fill in the yellow cells
Push the "Run Leggett" button
When the dos window running Leggett disappears, press the message box button

User Input | Calculation | Final Calculation used in Leggett

Directory for Leggett model, input, and output files	C:\Documents and Settings\06157\My Documents\OPPT 2010\Legett

Dust and Soil Uptake Section

	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Fraction of time spent in the home	0.82	0.82	0.79	0.77	0.76	0.73	0.7	0.69
Fraction of dust intake from floor	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99

Dust concentration, floor, home (µg/g)	34.4
Dust concentration, sill, home (µg/g)	166.8
Dust concentration, floor, outside the home (µg/g)	34.4
Dust concentration, sill, outside the home (µg/g)	166.8
Dust absorption fraction	0.5

Soil concentration, home (µg/g)	29
Soil concentration, outside the home (µg/g)	29
Soil absorption fraction	0.3

Fraction of soil + dust intake which is soil	0.45

	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Dust + soil intake (g/day)	0.06	0.06	0.11	0.11	0.11	0.11	0.11	0.11

	Child Age (years)							
Uptake from home dust (µg/day)	0.48	0.48	0.85	0.83	0.82	0.79	0.76	0.75
Uptake from out of home dust (µg/day)	0.11	0.11	0.23	0.25	0.26	0.29	0.32	0.34
Uptake from all dust (µg/day)	0.59	0.59	1.08	1.08	1.08	1.08	1.08	1.08

	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Uptake from home soil (µg/day)	0.19	0.19	0.34	0.33	0.33	0.31	0.30	0.30
Uptake from out of home soil (µg/day)	0.04	0.04	0.09	0.10	0.10	0.12	0.13	0.13
Uptake from all soil (µg/day)	0.23	0.23	0.43	0.43	0.43	0.43	0.43	0.43

Dietary Uptake Section

Dietary absorption fraction	0.5

	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Dietary lead intake (µg/day)	3.16	3.16	2.6	2.87	2.74	2.61	2.74	2.99
	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Uptake from diet (µg/day)	1.58	1.58	1.30	1.44	1.37	1.31	1.37	1.50

Water Uptake Section

Water lead concentration (µg/L)	4.61
Water absorption fraction	0.5

	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Water consumption (L/day)	0.36	0.36	0.271	0.317	0.349	0.38	0.397	0.414
	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Uptake from water (µg/day)	0.8298	0.8298	0.624655	0.730685	0.804445	0.8759	0.915085	0.95427

Inhalation Uptake Section

Air concentration ($\mu g/m^3$)	0.01							
	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Ventilation rate (m^3/day)	5.4	5.4	8	9.5	10.9	10.9	10.9	12.4
Lung absorption fraction (unitless)	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42
	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Uptake from air (μg/day)	0.023	0.023	0.034	0.040	0.046	0.046	0.046	0.052

Maternal Blood Lead Section

Maternal Blood Lead (μg/dL)	0.847

Uptakes for Leggett Model

	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Total Ingestion Uptake (μg/day)	3.23	3.23	3.44	3.68	3.69	3.69	3.80	3.96

	Child Age (years)							
	0-0.5	**0.5-1**	**1-2**	**2-3**	**3-4**	**4-5**	**5-6**	**6-7**
Total Inhalation Uptake (μg/day)	0.023	0.023	0.034	0.040	0.046	0.046	0.046	0.052

Appendix D

Geometric Mean Blood-Lead Values and Estimated Proportions of Children with Blood-Lead Concentrations above Target Levels

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Scenario Definitions for Regression Model Blood Lead Predictions

Dixon et al. (2009)			
Central Tendency Scenario		**Upper-End Scenario**	
Variable Value		**Variable**	**Value**
Sill Dust	6 ug/ sq.ft.	Sill Dust	6 ug/ sq.ft.
Age	1.5 years	Age	1.5 years
Ethnicity	Not nhblack	Ethnicity	**nhblack**
Date of Construction	1960-1977	Date of Construction	1960-1977
Poverty-Income Rat.	1.1	Poverty-Income Rat.	1.1
Born	US	Born	**Other**
Type	attached house	Type	mobile home
Smoker	no	Smoker	**yes**
cot. Missing	yes	cot. Missing	yes
Window repl (pre-78)	no	Window repl (pre-78)	no
Floor smooth	yes	Floor smooth	**no**

NHANES QL Model			
Empirical = Dust concentrations calculated with empirical (regression) model			
Mechanistic = Dust concentrations calculated with mechanistic model			
Central Tendency Scenario		**Upper-End Scenario**	
Variable Value		**Variable**	**Value**
Sill Dust	6 ug/ sq.ft.	Sill Dust	6 ug/ sq.ft.
Age	1.5 years	Age	1.5 years
Ethnicity	Not nhblack	Ethnicity	**nhblack**
Poverty-Income Rat.	1.1	Poverty-Income Rat.	1.1
Date of Construction	not pre-1940	Date of Construction	pre-1940
Floor Condition	smooth, cleanable	Floor Condition	not smooth and cleanable
Smokers in Home	No	Smokers in Home	No

Input parameter values for non-dust and soil blood lead exposure pathways for the biokinetic models are shown in Tables 4-1 through 4-3.

Predictions based on Dixon et al. Regression, CT Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	3.8	4.4	4.9	5.1	5.2
10	3.9	4.5	5.0	5.2	5.3
20	4.0	4.6	5.1	5.3	5.4
30	4.0	4.6	5.2	5.4	5.5
40	4.1	4.7	5.2	5.4	5.5

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	33%	42%	49%	51%	52%
10	35%	44%	50%	53%	54%
20	36%	45%	51%	54%	55%
30	37%	45%	52%	55%	56%
40	37%	46%	53%	55%	56%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	74%	81%	85%	87%	87%
10	76%	82%	86%	88%	88%
20	76%	83%	87%	88%	89%
30	77%	83%	87%	88%	89%
40	77%	84%	87%	89%	89%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	98%	99%	99%	99%	99%
10	98%	99%	99%	100%	100%
20	98%	99%	99%	100%	100%
30	98%	99%	99%	100%	100%
40	99%	99%	99%	100%	100%

Predictions based on Dixon et al. Regression, CT Scenario + nhBlack

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	5.0	5.8	6.4	6.7	6.8
10	5.1	5.9	6.6	6.9	7.0
20	5.2	6.0	6.7	7.0	7.1
30	5.3	6.1	6.8	7.1	7.2
40	5.3	6.2	6.9	7.2	7.3

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	50%	59%	65%	68%	68%
10	52%	60%	67%	69%	70%
20	53%	61%	68%	70%	71%
30	53%	62%	68%	71%	72%
40	54%	63%	69%	71%	72%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	86%	90%	93%	94%	94%
10	87%	91%	94%	94%	95%
20	87%	91%	94%	95%	95%
30	88%	92%	94%	95%	95%
40	88%	92%	94%	95%	95%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	99%	100%	100%	100%	100%
10	99%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on Dixon et al. Regression, Upper-End Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	8.1	9.6	10.2	9.9	9.3
10	8.4	9.9	10.5	10.2	9.6
20	8.5	10.1	10.7	10.4	9.8
30	8.6	10.2	10.8	10.5	9.9
40	8.7	10.3	10.9	10.6	10.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	78%	85%	87%	86%	83%
10	79%	86%	88%	87%	85%
20	80%	86%	88%	87%	85%
30	80%	87%	89%	88%	86%
40	81%	87%	89%	88%	86%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	97%	98%	99%	98%	98%
10	97%	98%	99%	99%	98%
20	97%	99%	99%	99%	98%
30	97%	99%	99%	99%	98%
40	97%	99%	99%	99%	98%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	100%	100%	100%	100%	100%
10	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Empirical Dust Conc.), CT Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	4.1	4.2	4.2	4.3	4.4
10	5.3	5.4	5.4	5.5	5.5
20	7.1	7.2	7.3	7.3	7.4
30	8.7	8.7	8.8	8.9	8.9
40	10.0	10.1	10.2	10.2	10.3

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	38%	39%	40%	41%	41%
10	53%	54%	55%	56%	56%
20	71%	72%	72%	72%	73%
30	80%	81%	81%	81%	82%
40	86%	86%	87%	87%	87%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	78%	79%	80%	80%	81%
10	88%	88%	89%	89%	89%
20	95%	95%	95%	95%	95%
30	97%	97%	98%	98%	98%
40	98%	99%	99%	99%	99%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	99%	99%	99%	99%	99%
10	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Mechanistic Dust Conc.), CT Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	3.7	3.8	3.8	3.9	3.9
10	5.2	5.2	5.3	5.3	5.3
20	8.0	8.1	8.1	8.1	8.2
30	10.8	10.9	10.9	11.0	11.0
40	13.7	13.7	13.8	13.8	13.9

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	33%	33%	34%	35%	35%
10	52%	53%	53%	54%	54%
20	77%	77%	77%	78%	78%
30	89%	89%	89%	89%	89%
40	94%	94%	94%	94%	94%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	74%	74%	75%	75%	76%
10	87%	87%	88%	88%	88%
20	97%	97%	97%	97%	97%
30	99%	99%	99%	99%	99%
40	100%	100%	100%	100%	100%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	98%	98%	98%	98%	98%
10	99%	99%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Empirical Dust Conc.), Upper End Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	6.0	6.1	6.2	6.2	6.3
10	7.7	7.8	7.9	7.9	8.0
20	10.5	10.6	10.6	10.7	10.7
30	12.7	12.8	12.9	12.9	13.0
40	14.8	14.8	14.9	15.0	15.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	61%	62%	63%	63%	64%
10	75%	76%	76%	76%	77%
20	88%	88%	88%	88%	88%
30	93%	93%	93%	93%	93%
40	95%	95%	96%	96%	96%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	91%	92%	92%	92%	92%
10	96%	96%	96%	96%	97%
20	99%	99%	99%	99%	99%
30	99%	99%	99%	99%	99%
40	100%	100%	100%	100%	100%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	100%	100%	100%	100%	100%
10	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Mechanistic Dust Conc.), Upper End Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	5.8	5.9	5.9	6.0	6.0
10	8.1	8.2	8.2	8.3	8.3
20	12.7	12.8	12.8	12.8	12.9
30	17.3	17.3	17.4	17.4	17.5
40	21.9	21.9	21.9	22.0	22.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	60%	60%	60%	61%	61%
10	78%	78%	78%	78%	79%
20	93%	93%	93%	93%	93%
30	97%	97%	97%	97%	97%
40	99%	99%	99%	99%	99%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	91%	91%	91%	91%	91%
10	97%	97%	97%	97%	97%
20	99%	99%	99%	99%	99%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	100%	100%	100%	100%	100%
10	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on IEUBK Model, Baseline Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	2.4	2.5	2.6	2.7	2.7
10	3.1	3.2	3.3	3.3	3.4
20	4.2	4.3	4.3	4.4	4.4
30	5.1	5.2	5.2	5.2	5.3
40	5.9	5.9	5.9	6.0	6.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	13%	14%	15%	16%	17%
10	23%	24%	25%	26%	27%
20	40%	40%	41%	42%	42%
30	51%	52%	52%	53%	53%
40	60%	60%	60%	61%	61%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	48%	50%	52%	54%	56%
10	64%	65%	66%	67%	68%
20	79%	80%	80%	81%	81%
30	87%	87%	87%	87%	88%
40	91%	91%	91%	91%	91%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	92%	92%	93%	94%	94%
10	96%	97%	97%	97%	97%
20	99%	99%	99%	99%	99%
30	99%	99%	99%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on Leggett Model, Baseline Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	7.07	9.19	12.54	15.34	17.82
10	7.16	9.29	12.64	15.43	17.92
20	7.24	9.37	12.72	15.51	18.00
30	7.32	9.44	12.79	15.59	18.07
40	7.38	9.51	12.86	15.65	18.14

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	71%	83%	92%	96%	98%
10	71%	83%	93%	96%	98%
20	72%	84%	93%	96%	98%
30	72%	84%	93%	96%	98%
40	73%	84%	93%	96%	98%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	95%	98%	99%	100%	100%
10	95%	98%	99%	100%	100%
20	95%	98%	99%	100%	100%
30	95%	98%	99%	100%	100%
40	95%	98%	99%	100%	100%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	100%	100%	100%	100%	100%
10	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on Dixon et al. Regression, CT Scenario

GSD =	2.1

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	3.8	4.4	4.9	5.1	5.2
10	3.9	4.5	5.0	5.2	5.3
20	4.0	4.6	5.1	5.3	5.4
30	4.0	4.6	5.2	5.4	5.5
40	4.1	4.7	5.2	5.4	5.5

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	36%	43%	49%	51%	52%
10	37%	44%	50%	52%	53%
20	38%	45%	51%	53%	54%
30	38%	46%	52%	54%	55%
40	39%	46%	52%	55%	55%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	71%	78%	82%	83%	84%
10	73%	79%	83%	84%	85%
20	73%	79%	83%	85%	85%
30	74%	80%	84%	85%	85%
40	74%	80%	84%	85%	86%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	96%	98%	98%	99%	99%
10	97%	98%	99%	99%	99%
20	97%	98%	99%	99%	99%
30	97%	98%	99%	99%	99%
40	97%	98%	99%	99%	99%

Predictions based on Dixon et al. Regression, CT Scenario + nhBlack

GSD =	2.1

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	5.0	5.8	6.4	6.7	6.8
10	5.1	5.9	6.6	6.9	7.0
20	5.2	6.0	6.7	7.0	7.1
30	5.3	6.1	6.8	7.1	7.2
40	5.3	6.2	6.9	7.2	7.3

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	50%	58%	63%	65%	66%
10	51%	59%	65%	67%	68%
20	52%	60%	66%	68%	68%
30	53%	61%	66%	68%	69%
40	53%	61%	67%	69%	69%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	82%	87%	90%	91%	91%
10	83%	88%	91%	91%	92%
20	84%	88%	91%	92%	92%
30	84%	89%	91%	92%	92%
40	85%	89%	91%	92%	92%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	98%	99%	99%	99%	100%
10	99%	99%	99%	100%	100%
20	99%	99%	99%	100%	100%
30	99%	99%	100%	100%	100%
40	99%	99%	100%	100%	100%

Predictions based on Dixon et al. Regression, Upper-End Scenario

GSD =	2.1

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	8.1	9.6	10.2	9.9	9.3
10	8.4	9.9	10.5	10.2	9.6
20	8.5	10.1	10.7	10.4	9.8
30	8.6	10.2	10.8	10.5	9.9
40	8.7	10.3	10.9	10.6	10.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	74%	81%	83%	82%	80%
10	76%	82%	84%	83%	81%
20	76%	83%	85%	84%	82%
30	77%	83%	85%	84%	82%
40	77%	84%	85%	84%	82%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	94%	97%	97%	97%	96%
10	95%	97%	97%	97%	97%
20	95%	97%	97%	97%	97%
30	95%	97%	98%	97%	97%
40	95%	97%	98%	97%	97%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	100%	100%	100%	100%	100%
10	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Empirical Dust Conc.), CT Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	4.1	4.2	4.2	4.3	4.4
10	5.3	5.4	5.4	5.5	5.5
20	7.1	7.2	7.3	7.3	7.4
30	8.7	8.7	8.8	8.9	8.9
40	10.0	10.1	10.2	10.2	10.3

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	40%	40%	41%	42%	43%
10	53%	54%	54%	55%	55%
20	68%	69%	69%	70%	70%
30	77%	77%	78%	78%	78%
40	83%	83%	83%	83%	83%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	75%	76%	76%	77%	77%
10	84%	85%	85%	85%	86%
20	92%	92%	92%	93%	93%
30	95%	95%	96%	96%	96%
40	97%	97%	97%	97%	97%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	97%	97%	97%	98%	98%
10	99%	99%	99%	99%	99%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Mechanistic Dust Conc.), CT Scenario

GSD =	2.1

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	3.7	3.8	3.8	3.9	3.9
10	5.2	5.2	5.3	5.3	5.3
20	8.0	8.1	8.1	8.1	8.2
30	10.8	10.9	10.9	11.0	11.0
40	13.7	13.7	13.8	13.8	13.9

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	35%	35%	36%	37%	37%
10	52%	52%	53%	53%	53%
20	74%	74%	74%	74%	75%
30	85%	85%	85%	86%	86%
40	91%	91%	91%	91%	92%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	71%	71%	72%	72%	73%
10	84%	84%	84%	84%	85%
20	94%	94%	94%	94%	94%
30	98%	98%	98%	98%	98%
40	99%	99%	99%	99%	99%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	96%	96%	96%	97%	97%
10	99%	99%	99%	99%	99%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Empirical Dust Conc.), Upper End Scenario

GSD =	2.1

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	6.0	6.1	6.2	6.2	6.3
10	7.7	7.8	7.9	7.9	8.0
20	10.5	10.6	10.6	10.7	10.7
30	12.7	12.8	12.9	12.9	13.0
40	14.8	14.8	14.9	15.0	15.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	60%	61%	61%	62%	62%
10	72%	73%	73%	73%	74%
20	84%	84%	84%	85%	85%
30	90%	90%	90%	90%	90%
40	93%	93%	93%	93%	93%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	88%	89%	89%	89%	89%
10	94%	94%	94%	94%	94%
20	97%	97%	97%	97%	98%
30	99%	99%	99%	99%	99%
40	99%	99%	99%	99%	99%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	99%	99%	99%	99%	99%
10	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Mechanistic Dust Conc.), Upper End Scenario

GSD =	2.1

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	5.8	5.9	5.9	6.0	6.0
10	8.1	8.2	8.2	8.3	8.3
20	12.7	12.8	12.8	12.8	12.9
30	17.3	17.3	17.4	17.4	17.5
40	21.9	21.9	21.9	22.0	22.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	58%	59%	59%	59%	60%
10	74%	75%	75%	75%	75%
20	90%	90%	90%	90%	90%
30	95%	95%	95%	95%	95%
40	98%	98%	98%	98%	98%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	87%	88%	88%	88%	88%
10	94%	94%	95%	95%	95%
20	99%	99%	99%	99%	99%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	99%	99%	99%	99%	99%
10	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on IEUBK Model, Baseline Scenario

GSD =	2.1

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	2.4	2.5	2.6	2.7	2.7
10	3.1	3.2	3.3	3.3	3.4
20	4.2	4.3	4.3	4.4	4.4
30	5.1	5.2	5.2	5.2	5.3
40	5.9	5.9	5.9	6.0	6.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	17%	18%	19%	20%	21%
10	27%	28%	28%	29%	30%
20	41%	42%	42%	43%	43%
30	51%	52%	52%	52%	53%
40	58%	59%	59%	59%	60%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	48%	50%	52%	53%	55%
10	62%	63%	64%	65%	66%
20	76%	77%	77%	78%	78%
30	83%	84%	84%	84%	84%
40	87%	88%	88%	88%	88%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	88%	89%	90%	91%	91%
10	94%	94%	94%	95%	95%
20	97%	97%	98%	98%	98%
30	99%	99%	99%	99%	99%
40	99%	99%	99%	99%	99%

Predictions based on Leggett Model, Baseline Scenario

GSD =	2.1

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	7.07	9.19	12.54	15.34	17.82
10	7.16	9.29	12.64	15.43	17.92
20	7.24	9.37	12.72	15.51	18.00
30	7.32	9.44	12.79	15.59	18.07
40	7.38	9.51	12.86	15.65	18.14

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	68%	79%	89%	93%	96%
10	69%	80%	89%	94%	96%
20	69%	80%	90%	94%	96%
30	70%	80%	90%	94%	96%
40	70%	81%	90%	94%	96%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	92%	96%	99%	99%	100%
10	92%	96%	99%	99%	100%
20	92%	96%	99%	99%	100%
30	93%	96%	99%	99%	100%
40	93%	96%	99%	99%	100%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	100%	100%	100%	100%	100%
10	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on Dixon et al. Regression, CT Scenario

GSD =	2.3

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	3.8	4.4	4.9	5.1	5.2
10	3.9	4.5	5.0	5.2	5.3
20	4.0	4.6	5.1	5.3	5.4
30	4.0	4.6	5.2	5.4	5.5
40	4.1	4.7	5.2	5.4	5.5

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	37%	44%	49%	51%	52%
10	38%	45%	50%	52%	53%
20	39%	46%	51%	53%	54%
30	40%	46%	52%	54%	54%
40	40%	47%	52%	54%	55%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	69%	75%	79%	80%	81%
10	70%	76%	80%	81%	82%
20	71%	77%	80%	82%	82%
30	72%	77%	81%	82%	83%
40	72%	77%	81%	82%	83%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	95%	96%	97%	97%	98%
10	95%	96%	97%	98%	98%
20	95%	97%	97%	98%	98%
30	95%	97%	98%	98%	98%
40	95%	97%	98%	98%	98%

Predictions based on Dixon et al. Regression, CT Scenario + nhBlack

GSD =	2.3

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	5.0	5.8	6.4	6.7	6.8
10	5.1	5.9	6.6	6.9	7.0
20	5.2	6.0	6.7	7.0	7.1
30	5.3	6.1	6.8	7.1	7.2
40	5.3	6.2	6.9	7.2	7.3

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	50%	57%	62%	64%	64%
10	51%	58%	63%	65%	66%
20	52%	59%	64%	66%	66%
30	53%	59%	64%	66%	67%
40	53%	60%	65%	67%	67%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	80%	84%	87%	88%	89%
10	81%	85%	88%	89%	89%
20	81%	85%	88%	89%	90%
30	82%	86%	89%	89%	90%
40	82%	86%	89%	90%	90%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	97%	98%	99%	99%	99%
10	98%	98%	99%	99%	99%
20	98%	98%	99%	99%	99%
30	98%	99%	99%	99%	99%
40	98%	99%	99%	99%	99%

Predictions based on Dixon et al. Regression, Upper-End Scenario

GSD =	2.3

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	8.1	9.6	10.2	9.9	9.3
10	8.4	9.9	10.5	10.2	9.6
20	8.5	10.1	10.7	10.4	9.8
30	8.6	10.2	10.8	10.5	9.9
40	8.7	10.3	10.9	10.6	10.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	72%	78%	80%	79%	77%
10	73%	79%	81%	80%	78%
20	74%	80%	82%	81%	79%
30	74%	80%	82%	81%	79%
40	75%	81%	83%	82%	80%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	92%	95%	95%	95%	94%
10	93%	95%	96%	95%	95%
20	93%	95%	96%	96%	95%
30	93%	95%	96%	96%	95%
40	93%	96%	96%	96%	95%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	99%	100%	100%	100%	100%
10	99%	100%	100%	100%	100%
20	99%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Empirical Dust Conc.), CT Scenario

GSD =	1.9

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	4.1	4.2	4.2	4.3	4.4
10	5.3	5.4	5.4	5.5	5.5
20	7.1	7.2	7.3	7.3	7.4
30	8.7	8.7	8.8	8.9	8.9
40	10.0	10.1	10.2	10.2	10.3

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	41%	42%	42%	43%	43%
10	53%	53%	54%	54%	55%
20	66%	67%	67%	68%	68%
30	75%	75%	75%	75%	76%
40	80%	80%	80%	81%	81%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	72%	73%	74%	74%	75%
10	82%	82%	82%	83%	83%
20	90%	90%	90%	90%	90%
30	93%	93%	93%	94%	94%
40	95%	95%	95%	95%	96%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	96%	96%	96%	96%	96%
10	98%	98%	98%	98%	98%
20	99%	99%	99%	99%	99%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Mechanistic Dust Conc.), CT Scenario

GSD =	2.3

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	3.7	3.8	3.8	3.9	3.9
10	5.2	5.2	5.3	5.3	5.3
20	8.0	8.1	8.1	8.1	8.2
30	10.8	10.9	10.9	11.0	11.0
40	13.7	13.7	13.8	13.8	13.9

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	36%	37%	37%	38%	38%
10	52%	52%	52%	53%	53%
20	71%	72%	72%	72%	72%
30	82%	83%	83%	83%	83%
40	89%	89%	89%	89%	89%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	69%	69%	70%	70%	70%
10	81%	81%	81%	82%	82%
20	92%	92%	92%	92%	92%
30	96%	96%	96%	96%	96%
40	98%	98%	98%	98%	98%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	94%	95%	95%	95%	95%
10	98%	98%	98%	98%	98%
20	99%	99%	99%	99%	99%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Empirical Dust Conc.), Upper End Scenario

GSD =	2.3

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	6.0	6.1	6.2	6.2	6.3
10	7.7	7.8	7.9	7.9	8.0
20	10.5	10.6	10.6	10.7	10.7
30	12.7	12.8	12.9	12.9	13.0
40	14.8	14.8	14.9	15.0	15.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	59%	59%	60%	60%	61%
10	70%	70%	71%	71%	71%
20	81%	82%	82%	82%	82%
30	87%	87%	87%	87%	87%
40	90%	90%	91%	91%	91%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	85%	86%	86%	86%	87%
10	91%	91%	92%	92%	92%
20	96%	96%	96%	96%	96%
30	97%	98%	98%	98%	98%
40	98%	98%	98%	98%	98%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	98%	99%	99%	99%	99%
10	99%	99%	99%	99%	99%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on NHANES QL Model (Mechanistic Dust Conc.), Upper End Scenario

GSD =	2.3

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	5.8	5.9	5.9	6.0	6.0
10	8.1	8.2	8.2	8.3	8.3
20	12.7	12.8	12.8	12.8	12.9
30	17.3	17.3	17.4	17.4	17.5
40	21.9	21.9	21.9	22.0	22.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	57%	58%	58%	58%	59%
10	72%	72%	72%	73%	73%
20	87%	87%	87%	87%	87%
30	93%	93%	93%	93%	93%
40	96%	96%	96%	96%	96%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	85%	85%	85%	85%	85%
10	92%	92%	92%	92%	93%
20	97%	97%	98%	98%	98%
30	99%	99%	99%	99%	99%
40	100%	100%	100%	100%	100%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	98%	98%	98%	98%	98%
10	99%	99%	99%	99%	99%
20	100%	100%	100%	100%	100%
30	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%

Predictions based on IEUBK Model, Baseline Scenario

GSD =	2.3

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	2.4	2.5	2.6	2.7	2.7
10	3.1	3.2	3.3	3.3	3.4
20	4.2	4.3	4.3	4.4	4.4
30	5.1	5.2	5.2	5.2	5.3
40	5.9	5.9	5.9	6.0	6.0

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	19%	20%	21%	22%	24%
10	29%	30%	31%	31%	32%
20	42%	43%	43%	44%	44%
30	51%	52%	52%	52%	53%
40	58%	58%	58%	58%	59%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	49%	50%	52%	53%	54%
10	61%	62%	63%	63%	64%
20	74%	74%	75%	75%	75%
30	80%	81%	81%	81%	82%
40	85%	85%	85%	85%	85%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	86%	87%	87%	88%	89%
10	92%	92%	92%	93%	93%
20	96%	96%	96%	96%	96%
30	97%	98%	98%	98%	98%
40	98%	98%	98%	98%	98%

Predictions based on Leggett Model, Baseline Scenario

GSD =	2.3

Geom. Mean	Sill				
Floor	50	100	150	200	250
5	7.07	9.19	12.54	15.34	17.82
10	7.16	9.29	12.64	15.43	17.92
20	7.24	9.37	12.72	15.51	18.00
30	7.32	9.44	12.79	15.59	18.07
40	7.38	9.51	12.86	15.65	18.14

>5 ug/dl	Sill				
Floor	50	100	150	200	250
5	66%	77%	87%	91%	94%
10	67%	77%	87%	91%	94%
20	67%	77%	87%	91%	94%
30	68%	78%	87%	91%	94%
40	68%	78%	87%	91%	94%

>2.5 ug/L	Sill				
Floor	50	100	150	200	250
5	89%	94%	97%	99%	99%
10	90%	94%	97%	99%	99%
20	90%	94%	97%	99%	99%
30	90%	94%	98%	99%	99%
40	90%	95%	98%	99%	99%

>1 ug/l	Sill				
Floor	50	100	150	200	250
5	99%	100%	100%	100%	100%
10	99%	100%	100%	100%	100%
20	99%	100%	100%	100%	100%
30	99%	100%	100%	100%	100%
40	99%	100%	100%	100%	100%

Dixon et al. (2009) Regression Model		
Variable	**Coefficient**	**Variable Value, Central Tendency***
Intercept	-0.517	1
Age (years)	2.62	2.5
Age^2	-1.353	6.25
Age^3	0.273	15.625
Age^4	-0.019	39.0625
Date of construction missing	-0.121	0
Date of construction post-1990	-0.198	0
Date of construction 1978-89	-0.196	0
Date of construction 1960-77	-0.174	1
Date of construction 1950-59	-0.207	0
Date of construction 1940-49	-0.0012	0
Date of construction pre-1940	0	0
Family income relative to poverty missing	0.053	0
Family income relative to poverty	-0.053	1.1
Ethnicity = non-Hispanic white	0	1
Ethnicity = non-Hispanic black	0.274	0*
Ethnicity = Hispanic	-0.035	0
Ethnicity = Other	0.128	0
Country of Birth missing	-0.077	0
Country of Birth = U.S.	0	1
Country of Birth = Mexico	0.353	0
Country of Birth = Other	0.154	0*
Type of Unit = Missing	-0.064	0
Type of Unit = Mobile Home	0.127	0*
Type of Unit = Detached House	-0.025	0
Type of Unit = Attached House	0	1
Type of Unit = Apartment Building (1-9 units)	0.069	0
Type of Unit = Apartment Building (10+ units)	-0.133	0
Smokers in HouseHold = missing	0.138	0
Smokers in Household = yes (1 or more)	0.1	0*
Smokers in Household = no	0	0
Serum Continine Missing	-0.15	1
cot	0.039	0
Window replacement in pre-1978 home = missing	-0.008	0
Window replacement in pre-1978 home = yes	0.097	0
Window replacement in pre-1978 home = no	0	0
Floor condition missing	0.178	0
Floor not smooth and cleanable X floor dust loading, μ/ft^2	0.386	Weighted average†
Floor smooth and cleanable X floor dust loading, μ/ft^2	0.205	Weighted average†
Floor not smooth and cleanable X floor dust loading ^{2}	0.023	Weighted average†
Floor smooth and cleanable X floor dust loading ^{3}	0.027	Weighted average†
Floor not smooth and cleanable X floor dust loading ^{3}	-0.02	Weighted average†
Floor smooth and cleanable X floor dust loading ^{3}	-0.009	Weighted average†
windowsill dust loading missing	0.053	Weighted average†
windowsill dust loading	0.041	Weighted average†
* Upper end predictions assume child is non-Hispanic Black, born in "other" country, living in a mobile home with floors that are not smooth and cleanable with one or more smokers		
† Weighted average floor dust loading calculated assuming 92.7 percent of time is spent in residences, 3.4 percent in COFs, and 3.9 percent in public and commercial buildings (see Section 4.1.2)		

NHANES Quasi-Likelihood Regression Model		
Variable	**Coefficient**	**Variable Value, Central Tendency***
Intercept	0.41	1
Ethnicity = non-Hispanic black	0.70	0*
Age (months)	0.14	18
Age^2	-0.0046	324
Age^3	0.000043	5832
Family income relative to poverty	-0.16	1.1
Date of construction pre-1940	0.49	0*
Smokers in Household = yes (1 or more)	0.50	0
Floor smooth and cleanable	0.27	1*
Floor dust lead concentration‡	0.027	Weighted average†
Windowsill dust lead concentration‡	0.00022	Weighted average†
Floor dust lead concentration X Floor smooth and cleanable‡	-0.0071	Weighted average†
Floor dust lead concentration X Age‡	-0.00027	Weighted average†
* Upper End predictions assume child is non-Hispanic Black, living in a housing unit built before 1940 with floors that are not smooth and cleanable.		
† Weighted average floor dust concentrations calculated assuming 92.7 percent of time is spent in residences, 3.4 percent in COFs, and 3.9 percent in public and commercial buildings (see Section 4.1.2)		
‡ Floor dust concentrations calculated from NHANES dust loading measurements using "empirical" or mechanistic models, as described in Section 3.2.3		

Baseline Input Parameter Values for the IEUBK and Leggett Biokinetic Models								
	Child Age (years)							
Input Parameter	**0–0.5**	**0.5–1**	**1–2**	**2–3**	**3–4**	**4–5**	**5–6**	**6–7**
Fraction of time spent in the home	0.82	0.82	0.79	0.77	0.76	0.73	0.7	0.69
Fraction of dust exposure from windowsill	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Soil Exposure (Residence), μg/gm	29	29	29	29	29	29	29	29
Soil Exposure (Outside Residence), μg/gm	29	29	29	29	29	29	29	29
Dust concentration, floor, home (μg/g)	varied*†	varied	varied	varied	varied	varied	varied	varied
Dust concentration, sill, home (μg/g)	varied	varied	varied	varied	varied	varied	varied	varied
Dust concentration, floor, outside the home (μg/g)	60.5	60.5	60.5	60.5	60.5	60.5	60.5	60.5
Dust concentration, sill, outside the home (μg/g)	369	369	369	369	369	369	369	369
Soil absorption fraction	0.3							
Fraction of soil + dust intake that is soil	0.45							
Dust + soil intake (g/day)	0.06	0.06	0.11	0.11	0.11	0.11	0.11	0.11
Dietary lead intake (mg/day)	3.16	3.16	2.6	2.87	2.74	2.61	2.74	2.99
Dietary absorption fraction	0.5							
Water consumption (L/day)	0.36	0.36	0.27	0.32	0.35	0.38	0.40	0.41
Water lead concentration (mg/L)	4.61							
Water absorption fraction	0.5							
Ventilation rate (m^3/day)	5.4	5.4	8	9.5	10.9	10.9	10.9	12.4
Lung absorption fraction (unitless)	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42
Air concentration ($\mu g/m^3$)	0.01							
Maternal blood lead (mg/dL)	0.847							
* Concentration varied depending on hazard standard being evaluated								
†Floor dust concentrations calculated from NHANES dust loading measurements using "empirical" model (see Section 3.2.3)								

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Appendix E

Loading to Concentration Conversion Methods

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The indoor lead hazard standard prescribes the amount of lead allowed on the surface per unit area (lead loading). The biokinetic blood lead models, however, cannot accept lead loadings as inputs. Instead, they require the lead concentration, or the amount of lead per mass of dust. Additionally, as noted in section 3.2.3, this transformation of the observations allows a model consistent with linear low-dose biokinetics. Thus, dust loadings were converted to dust concentrations for input into the blood lead models. Two different estimates have been developed for this approach, based on two different methodologies: 1) an empirical (statistical regression) model and 2) a mechanistic model. Sections E.1 through E.3 describe these estimates and highlight the strengths and limitations of each.

E.1 Development of a Regression Equation

The National Survey of Lead-Based Paint in Housing ("HUD Survey Data") was used to develop a loading-to-concentration regression equation for this approach. The data, available in Appendix C-1 in a risk assessment (US EPA, 1998), provide information on wipe sample lead dust loadings, vacuum sample lead dust loadings, and blue nozzle lead concentrations on the floor for over 312 homes in different vintage categories: Pre1940, 1940-1959, 1960-1979, and Post1980. It is anticipated that the wipe samples better capture the total lead present in the home; the vacuum samples are subject to vacuum collection efficiencies. Thus, the wipe loadings were paired with the blue nozzle concentrations at each home to develop the loading-to-concentration statistical relationship. By doing so, the assumption is made that the concentration is roughly uniform across all particles and the particles collected by the blue nozzle device are representative of the true average concentration. In order to focus on the homes containing lead paint, only the data from the older three vintage categories were included. This eliminated 28 data points from the dataset. Some statistics from the reduced dataset are provided in Table E-1. In general, the spread in the data is large and covers loadings up to 375 $\mu g/ft^2$ and concentrations up to 50,400 $\mu g/g$. The range of candidate hazard standards is below the 95^{th} percentile loadings, so the results of the regression are anticipated to apply to the hazard standard in residences.

Table E-1. Statistics from the HUD Survey Data

	Loading ($\mu g/ft^2$)	Concentration ($\mu g/g$)
Average	20.99	559.08
Min	0.51	0.09
Max	375.00	50400.00
5^{th} percentile	1.25	33.85
25^{th} percentile	3.27	101.75
50^{th} percentile	7.43	201.00
75^{th} percentile	17.38	374.25
95^{th} percentile	96.10	1522.50

From the raw data, each loading and concentration was transformed by taking the natural log. Then, the regression was carried out using the untransformed variables and also the natural-log-transformed variables. Table E-2 shows the results of each regression.

Table E-2. Regression Analysis Results

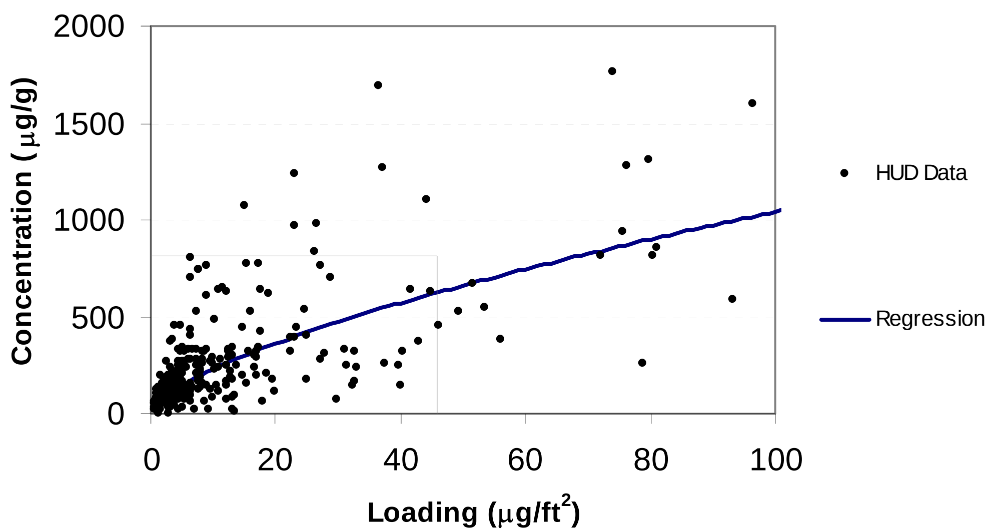
Data	Variable	Coefficient	Standard Error of Coefficient	t-stat	p-value	F-stat, p-level	Adjusted r2
Untransformed	Intercept	159.74	195.86	0.82	0.42	19.88, <0.0000	0.065
	Slope	19.02	4.26	4.46	<0.0000		
Natural-log-transformed	Intercept	3.93	0.10	38.11	<0.0000	246.75, <0.0000	0.465
	Slope	0.6655	0.42	15.71	<0.0000		

The data are positively skewed, and the regression analysis reveals that the log-transformed data provide a regression with a larger adjusted r^2 value. Thus, the log-transformed relationship is chosen, and after accounting for the natural log transformation, the equation relating concentration and loading is:

$$Concen = 50.96 \times Loading^{0.6553}$$

Figure E-1 below shows the raw data and the regression relationship. The gray line segments define a box at the 90th percentiles in the loading and the concentration.

Figure A-1. HUD Data and the Regression Relationship



E.2 Development of a Mechanistic Dust Model

The mechanistic model is designed to capture the physical transfer of mass from one medium to another under the assumption of mass balance. Previous studies have also built mass balance models of indoor dust. Allott et al. (1994) constructed a mass balance model to estimate the residence time of contaminated soil particles in the indoor environment based on observations in four homes in England contaminated by the Chernobyl incident. Thatcher and Layton (1995) constructed an indoor mass balance model of a home in California to estimate deposition rates, resuspension rates, and infiltration factors. Recognizing the key role of tracked-in soil on indoor dust loadings, Johnson (2008) built the DIRT model simulating the spatial pattern of tracked-in soil for a given total soil mass flux into the home. Layton and Beamer (2009) built a model simulating tracked-in soil and penetration of outdoor air and the subsequent physical processes governing indoor dust loadings. These models cannot be readily applied for developing an approach for the lead hazard standards, however, because they do not include any dust source from lead-containing paint. A new model was constructed for the hazard standard approach and the parameters were optimized against all available data, as described below. Where applicable, the resulting coefficients are compared to those found in the above studies to help frame the model in the existing literature. This mechanistic model is deterministic in its underlying nature.

The general form of the mass balance equation for a single compartment of interest is:

$$\frac{d[Mass]}{dt} = Flux\ of\ \ Mass\ In - Flux\ of\ \ Mass\ Out$$

where:

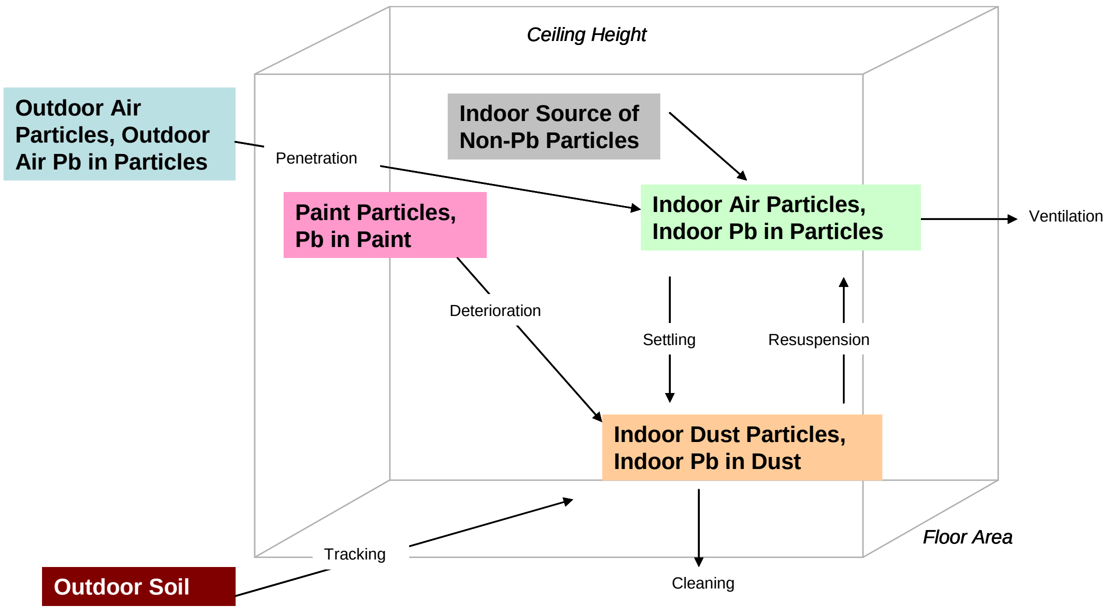
d[Mass]/dt	= change over time of the mass
Flux of Mass In	= flux of mass into the compartment
Flux of Mass Out	= flux of mass out of the compartment

In the dust model, two "compartments" of interest are defined: the indoor air and the floor. Both of these compartments will contain particulates associated with indoor dust, and by parameterizing the processes that govern the flux of mass to and from each compartment, the model can provide an inventory of dust in the air and on the floor through time.

In the above equation, "mass" could refer to either the mass of lead that penetrates the home and settles on the floor in the dust or it could refer to the mass of the dust particles themselves. Because the blood lead model needs inputs of lead dust concentration, the mechanistic model must separately account for both the mass of lead and the mass of dust particulate that accumulates on the floor. Then, by dividing the total lead mass by the total dust mass, the model provides an estimate of the average lead dust concentration. Thus, for each compartment there are two separate equations, one for the lead mass and one for the dust particulate mass.

The dominant sources of lead to the indoor dust are ambient air particles which penetrate the indoor environment and settle on the floor, outdoor soil particles which are tracked into the home, and lead-containing paint which flakes or chips off the walls and settles to the floor. Dust particles have the same sources, although non-lead dust particles are also formed indoors through human activities such as cooking and smoking and by the accumulation of human and pet dander. Figure E-2 shows a schematic of the various lead and particulate mass flux terms used in the mechanistic model to account for all sources and sinks of mass.

Figure E-2. Mechanistic Indoor Dust Model Schematic



For the indoor air compartment, the fluxes for mass include penetration of air and particles from outdoors, ventilation of indoor air back to the outdoor environment, deposition of mass out of the air, resuspension of accumulated mass on the floor back into the air, generation due to indoor sources (where cooking and smoking are thought to dominate these sources), and generation due to the formation of human and pet dander[f]:

$$\frac{dINAIR_{Pb}}{dt} = Penetration\ Flux_{Pb} - Ventilation\ Flux_{Pb} - Deposition\ Flux_{Pb} + Resuspension\ Flux_{Pb} + Indoor\ Sources_{Pb} + Dander\ Sources_{Pb}$$

$$\frac{dINAIR_{Part}}{dt} = Penetration\ Flux_{Part} - Ventilation\ Flux_{Part} - Deposition\ Flux_{Part} + Resuspension\ Flux_{Part} + Indoor\ Sources_{Part} + Dander\ Sources_{Part}$$

where:

[f] *The presence of an HVAC system will tend to recirculate indoor air, passing the air through a filter with each circulation. This system will tend to remove mass from the indoor environment (both in the air and on the floor) and act as a further sink. Because the circulation rate and filtration efficiency of such systems has not been comprehensively described in the literature and because use of such systems changes across the seasons and different geographic regions, removal of mass during recirculation is not included in the mechanistic model.*

$dINAIR_{Pb}/dt$ = change in time of the indoor air lead mass
$dINAIR_{Part}/dt$ = change in time of the indoor air particulate mass
Penetration Flux = penetration of air containing particles from outdoors
Ventilation Flux = ventilation of indoor air back to the outdoor environment
Deposition Flux = deposition of mass out of the air
Resuspension Flux = resuspension of accumulated mass on the floor back into the air
Indoor Sources = generation of mass due to indoor sources such as cooking or smoking
Dander Sources = generation of mass due to human and pet dander

In general, each flux is parameterized as either a constant source or as the mass of the "donor" compartment multiplied by the rate (expressed in reciprocal time) of the physical exchange process. In some cases, an efficiency factor is also included to account for any filtration of lead associated with the process. In addition, there is a separate flux term for the lead mass and for the particulate equations. For the *Penetration Flux*,

$$Penetration\ Flux_{Pb} = AER \times P \times PbAIR \times V$$

$$Penetration\ Flux_{Part} = AER \times P \times PartAIR \times V$$

where:

$Penetration\ Flux_{Pb}$ = penetration of air lead from outdoors (μg/h)
$Penetration\ Flux_{Part}$ = penetration of air particles from outdoors (g/h)
AER = air exchange rate (h^{-1})
P = penetration efficiency (unitless)
$PbAIR$ = concentration of lead in ambient air ($\mu g/m^3$)
$PartAIR$ = concentration of particles in ambient air (g/m^3)
V = volume of the house (m^3)

Because the air exchange rate (*AER*) specifies the number of times the indoor air is replaced by outdoor air in a given hour, it represents both the rate of penetration in and ventilation out. The ventilation flux out of the house is thus given by:

$$Ventilation\ Flux_{Pb} = AER \times INAIR_{Pb}$$

$$Ventilation\ Flux_{Part} = AER \times INAIR_{Part}$$

where:

$Ventilation\ Flux_{Pb}$ = ventilation of indoor lead in air back to the outdoor environment (μg/h)

$Ventilation\ Flux_{Part}$ = ventilation of indoor particulate in air back to the outdoor environment (g/h)

AER = air exchange rate (h^{-1})

$INAIR_{Pb}$ = indoor mass of lead in air (μg)

$INAIR_{Part}$ = indoor mass of particulate in air (g)

The deposition flux (*Deposition Flux*) is defined as the amount of mass in the air times a deposition rate:

$$Deposition\ Flux_{Pb} = D \times INAIR_{Pb}$$

$$Deposition\ Flux_{Part} = D \times INAIR_{Part}$$

where:

$Deposition\ Flux_{Pb}$ = deposition of lead out of the air (μg/h)

$Deposition\ Flux_{Part}$ = deposition of particulate out of the air (g/h)

D = deposition rate (h^{-1})

$INAIR_{Pb}$ = indoor mass of lead in air (μg)

$INAIR_{Part}$ = indoor mass of particulate in air (g)

For resuspension, the amount of resuspended material depends on the total available mass on the floor multiplied by a resuspension rate:

$$Resuspension\ Flux_{Pb} = R \times FLOOR_{Pb}$$

$$Resuspension\ Flux_{Part} = R \times FLOOR_{Part}$$

where:

$Resuspension\ Flux_{Pb}$ = resuspension of lead out of the air (μg/h)

$Resuspension\ Flux_{Part}$ = deposition of particulate out of the air (g/h)

R = deposition rate (h^{-1})

$FLOOR_{Pb}$ = mass of lead on the floor (μg)

$FLOOR_{Part}$ = mass of particulate on the floor (g)

For the indoor sources of mass, each source is set equal to a constant rate:

$$IndoorSources_{Pb} = 0$$

$$DanderSources_{Pb} = 0$$

$$IndoorSources_{Part} = CookingRate_{Part} + SmokingRate_{Part}$$

$$DanderSources_{Part} = DanderRate_{Part}$$

where:

$IndoorSources_{Pb}$ = source of lead due to cooking and smoking (μg/h); assumed to be zero.
$DanderSources_{Pb}$ = source of lead due to formation of dander (μg/h); assumed to be zero.
$IndoorSources_{Part}$ = source of particulate due to cooking and smoking (g/h)
$CookingRate_{Part}$ = rate of generation of particulate mass due to cooking (g/h)
$SmokingRate_{Part}$ = rate of generation of particulate mass due to smoking (g/h)
$DanderSources_{Part}$ = source of particulate due to formation of dander (g/h)
$DanderRate_{Part}$ = rate of generation of particulate mass due to dander (g/h)

So, using the penetration, ventilation, deposition fluxes, and indoor source terms, the equation for the change in time of the indoor air lead mass is:

$$\frac{dINAIR_{Pb}}{dt} = AER \times P \times PbAIR \times V - AER \times INAIR_{Pb} - D \times INAIR_{Pb} + R \times FLOOR_{Pb}$$

$$\frac{dINAIR_{Part}}{dt} = AER \times P \times PartAIR \times V - AER \times INAIR_{Part} - D \times INAIR_{Part} + R \times FLOOR_{Part} + CookingRate_{Part} + SmokingRate_{Part} + DanderRate_{Part}$$

where:

$dINAIR_{Pb}/dt$ = change in time of the indoor air lead mass (μg/h)
$dINAIR_{Part}/dt$ = change in time of the indoor air particulate mass (g/h)
$INAIPR_{Pb}$ = indoor mass of lead in air (μg)
$INAIPR_{Part}$ = indoor mass of particulate in air (μg)
$FLOOR_{Pb}$ = mass of lead on the floor (μg)
$FLOOR_{Part}$ = mass of particulate on the floor (g)
$PbAIR$ = concentration of lead in ambient air (μg/m^{3})
$PartAIR$ = concentration of particulate in ambient air (g/m^{3})
AER = air exchange rate (hour^{1})
P = penetration efficiency (unitless)
V = volume of the house (m^{3})

D = deposition rate (h^{-1})

R = resuspension rate (h^{-1})

$CookingRate_{Part}$ = rate of generation of particulate mass due to cooking (g/h)

$SmokingRate_{Part}$ = rate of generation of particulate mass due to smoking (g/h)

$DanderRate_{Part}$ = rate of generation of particulate mass due to dander (g/h)

For the indoor floor dust compartment (*FLOOR*), the fluxes include deposition of lead from the air onto the floor, resuspension of lead from the floor into the air, flaking of paint from the walls, tracking of lead from outdoor soil, and removal of lead due to routine cleaning:

$$\frac{dFLOOR_{Pb}}{dt} = Deposition\ Flux_{Pb} - Resuspension\ Flux_{Pb} + PaintFlux_{Pb} + TrackingFlux_{Pb} - Cleaning\ Flux_{Pb} \qquad \text{(Equation 1A)}$$

$$\frac{dFLOOR_{Part}}{dt} = Deposition\ Flux_{Part} - Resuspension\ Flux_{Part} + PaintFlux_{Part} + TrackingFlux_{Part} - Cleaning\ Flux_{Part} \qquad \text{(Equation 1B)}$$

where:

$dFLOOR/dt$ = change in time of the indoor floor mass

Deposition Flux = deposition of mass out of the air onto the floor

Resuspension Flux = resuspension of mass from the floor into the air

Paint Flux = flaking of lead-containing paint onto the floor

Tracking Flux = tracking of soil inside from outdoors

Cleaning Flux = removal of lead due to routine cleaning

The deposition flux (*Deposition Flux*) and resuspension flux (*ResuspensionFlux*) retain the same form as in the *INAIR* equations. The paint flux is parameterized using a paint chipping fraction, a wall area expressed as the wall loading multiplied by the house volume, and lead paint concentration for the lead mass and the same paint chipping fraction and wall area with a coverage density for the particulate mass. The chipping fraction is explicitly assumed to account for the mass that falls on the floor rather than any mass that lands on window sills or other surfaces:

$$Paint\ Flux_{Pb} = PbPaintConcen \times ChipFraction \times V \times WallLoading \times UnitConv$$

$$Paint\ Flux_{Part} = CoverageDens \times ChipFraction \times V \times WallLoading \times UnitConv$$

where:

$PaintFlux_{Pb}$ = generation of lead in air due to deterioration of lead-containing paint (μg/h)

$PaintFlux_{Part}$	= generation of particulate in air due to deterioration of lead-containing paint (μg/h)
$PbPaintConcen$	= lead concentration in the paint (mg/cm^2)
$ChipFraction$	= fraction of total wall area which flakes from the walls per year ($year^{-1}$)
V	= volume of the home (m^3)
$WallLoading$	= area of wall space per unit volume of the home (m^2/m^3)
$CoverageDens$	= the coverage density of paint on the wall (g/m^2)
$UnitConv$	= unit conversion necessary to make units consistent (1 year/8760 h)

The tracking flux (TrackingFlux) is parameterized specifically according to the limited data available about the process. Von Lindern et al. (2003) measured the amount of particulate deposited on front mats in 276 houses in two locations near the Bunker Hill Superfund Site. The lead levels reported in the paper are expected to be high-end and are not expected to represent general population exposures. This approach assumes, however, that the rate of accumulation of dust (as opposed to the lead in the dust) on doormats is not strongly affected by the location and can be used to represent a national population of homes. In addition, Thatcher and Layton (1995) measured the difference between particulate accumulation in tracked and untracked areas in the home as well as the amount on the front mat. From these two data sources, it is possible to estimate a distribution of mat particulate accumulation rates as well as the fraction of material that remains on the mat compared to being tracked into the home. For this reason, the tracking is parameterized as:

$$Tracking\ Flux_{Pb} = PbSoilConcen \times TrackingRate \times \frac{(1 - MatFrac)}{MatFrac}$$

$$Tracking\ Flux_{Part} = TrackingRate \times \frac{(1 - MatFrac)}{MatFrac}$$

where:

$TrackingFlux_{Pb}$	= accumulation of tracked-in lead on the floor (μg/h)
$TrackingFlux_{Part}$	= accumulation of tracked-in particulate on the floor (g/h)
$PbSoilConcen$	= concentration of lead in the tracked-in soil (μg/g)
$TrackingRate$	= rate at which particulate is deposited on front mats (g/h)
$MatFrac$	= fraction of total tracked material which is deposited on the front mat (as opposed to the remainder of the house) (unitless)

The cleaning flux (*Cleaning Flux*) is parameterized assuming a cleaning efficiency (*CE*) and cleaning frequency (*CF*) and multiplying these by the mass on the floor (*FLOOR*):

$$Cleaning\ Flux_{Pb} = CE \times CF \times FLOOR_{Pb}$$

$$Cleaning\ Flux_{Part} = CE \times CF \times FLOOR_{Part}$$

where:

$Cleaning\ Flux_{Pb}$ = removal of lead due to routine cleaning (μg/h)

$Cleaning\ Flux_{Part}$ = removal of particulate due to routine cleaning (g/h)

CE = cleaning efficiency (unitless)

CF = cleaning frequency (cleanings/h)

$FLOOR_{Pb}$ = mass of lead on the floor (μg)

$FLOOR_{Part}$ = mass of particulate on the floor (g)

In the above parameterization, the lead and particulate appear to be cleaned separately, although they are actually present on the same physical particles; by applying the same cleaning equation to both the mass of lead and the mass of particulate, the assumption is made that cleaning occurs over the whole floor and the concentration of lead on the particles is roughly uniform across all particles on the floor.

Combining the floor fluxes then gives:

$$\frac{dFLOOR_{Pb}}{dt} = D \times INAIR_{Pb} - R \times FLOOR_{Pb} + PbPaintConcen \times ChipFraction \times V \times WallLoading \times UnitConv + PbSoilConcen \times TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} - CE \times CF \times FLOOR_{Pb} \quad \text{(Equation 2A)}$$

$$\frac{dFLOOR_{Part}}{dt} = D \times INAIR_{Part} - R \times FLOOR_{Part} + PbCoverageDens \times ChipFraction \times V \times WallLoading \times UnitConv + TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} - CE \times CF \times FLOOR_{Part} \quad \text{(Equation 2B)}$$

where:

$dFLOOR_{Pb}/dt$ = change in time of the indoor floor lead mass (μg/h)

$dFLOOR_{Part}/dt$ = change in time of the indoor floor particulate mass (g/h)

$INAIPR_{Pb}$ = indoor mass of lead in air (μg)

$INAIPR_{Part}$ = indoor mass of particulate in air (μg)

$FLOOR_{Pb}$ = mass of lead on the floor (μg)

$FLOOR_{Part}$ = mass of particulate on the floor (g)

D = deposition rate (h^{-1})

R = resuspension rate (h^{-1})

$PbPaintConcen$ = lead concentration in the paint (mg/cm^2)

ChipFraction = fraction of total wall area which flakes from the walls per year ($year^{-1}$)

V = volume of the home (m^3)

WallLoading = area of wall space per unit volume of the home (m^2/m^3)

CoverageDens = the coverage density of paint on the wall (g/m^2)

UnitConv = unit conversion necessary to make units consistent (1 year/8760 h)

PbSoilConcen = concentration of lead in the tracked-in soil (µg/g)

TrackingRate = rate at which particulate is deposited on front mats (g/h)

MatFrac = fraction of total tracked material which is deposited on the front mat (as opposed to the remainder of the house) (unitless)

CE = cleaning efficiency (unitless)

CF = cleaning frequency (cleanings/h)

The above equations can be converted to difference equations by assuming a discrete time step and the model can be integrated forward in time to describe the lead and particulate accumulation at any moment. The derivation of the hazard standard, however, assumes that conditions in the home are relatively static, so the steady state solution to the above equations can capture the long-term air and floor lead and particulate masses. To obtain the steady-state solution for each compartment, the derivative terms are set to zero, so that nothing is changing in time. Using equations (1A) and (2A) to solve for the floor lead mass at steady state gives:

$$
\begin{aligned}
FLOOR_{Pb} = {} & \frac{1}{(R + CE \times CF)(AER + D) - RD} \times \\
& (PbPaintConcen \times ChipFraction \times V \times WallLoading \times UnitConv \times (AER + D) + \\
& PbSoilConcen \times TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} \times (AER + D) + \\
& PbAir \times D \times AER \times P \times V)
\end{aligned}
$$

This equation is linear with respect to the lead paint, soil, and outdoor air concentrations and gives the expected floor lead accumulation in the house at steady state. Similarly, using equations (1B) and (2B) to solve for the floor particulate mass at steady state gives:

$$
\begin{aligned}
FLOOR_{Part} = {} & \frac{1}{(R + CE \times CF)(AER + D) - RD} \times \\
& [CoverageDens \times ChipFraction \times V \times WallLoading \times UnitConv \times (AER + D) + \\
& TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} \times (AER + D) + \\
& PartAir \times D \times AER \times P \times V + \\
& D \times (CookingRate + SmokingRate + DanderRate)]
\end{aligned}
$$

In order to find the relationship between the floor loading and the concentration, we define the equation:

$$Loading = Slope \times Concen$$

By using the floor lead mass, the floor particulate mass, and the area of the house, the *slope* in the above equation is given by

$$\begin{aligned} slope = {} & \frac{1}{[(R + CE \times CF)(AER + D) - RD] \times V \times FloorLoading} \times \\ & [CoverageDens \times ChipFraction \times V \times WallLoading \times UnitConv \times (AER + D) + \\ & TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} \times (AER + D) + \\ & PartAir \times D \times AER \times P \times V + \\ & D \times (CookingRate + SmokingRate + DanderRate)] \end{aligned} \qquad \text{(Equation 3)}$$

This final equation is the conversion used in the approach to convert loadings to concentrations (and vice versa).

E.2.1 Input Values for the Mechanistic Model

Values were selected from the literature for input into the mechanistic model equations. Table E-3 lists all the input characteristics in the *slope* variable. The lead paint concentration, lead air concentration, and lead soil concentration are also needed for the calculation of loadings and concentrations, and these are adjusted according to the dataset being modeled. Each variable includes a central tendency estimate intended to be nationally representative. For variables where distribution information is available and implemented in the model, the geometric mean and geometric standard deviation from the estimated lognormal distribution are also shown.

The house volume (*V*) was taken from the 2001 Residential Energy Consumption Survey (RECS) (US DOE, 2001). Binned data were used to estimate the lognormal distribution, and the central tendency estimate is the mean of the calculated distribution. The wall loading (*WallLoading*) and floor loading (*FloorLoading*) were taken from the Exposure Factors Handbook (USEPA, 1997a).

The air exchange rate (*AER*) was taken from the Exposure Factors Handbook (USEPA 1997a) recommendation. Other information by time of year and region of the country is available, but these data have not been added to the model. The penetration efficiency (*P*) has been modeled for particles of various size classes and has been measured in a few field studies to be less than one (e.g., Dockery and Spengler, 1981; Freed et al., 1983; Liu and Nazaroff, 2001). Unlike the above studies, however, in a field study that simultaneously controlled for penetration and deposition, the penetration efficiency was found to be near 1 for all size classes (Thatcher and Layton, 1995); similar results were also reported for $PM_{2.5}$ for homes in California (Ozkaynak et al., 1996) and for a model of NHEXAS Midwest homes (P=0.96; Layton and Beamer, 2009). Thus, the penetration efficiency was set to 1 for the mechanistic model.

The deposition rate (*D*) was set to 0.65 h^{-1} based on information in the Exposure Factors Handbook (USEPA, 1997a) based on a paper by Wallace (1996). The value for PM_{10} was selected, as most of the suspended particulate in the home is expected to fall within this size range.

The resuspension rate (*R*) varies strongly according to what activity is being undertaken in the home. Resuspension rates during periods where humans are still or absent are lower than during periods of human activity. Vacuuming, in particular, introduces much higher resuspension. For the approach model, an intermediate value was taken from values calculated in Layton and Beamer (2009) for homes in the NHEXAS Midwest region (1.4×10^{-4} h^{-1}). This value incorporates the increased resuspension rate during an episode when one person was walking through the room.

An extensive literature review was conducted, but no information could be found for typical paint chipping rates in homes. A few approaches were implemented in the model, including a constant rate, a rate that was exponential in time, and a rate that depended on the overall wall area. Based on a review of the results of the calibration exercise and further review of the physical processes, the latter approach was selected. The chipping fraction was then found by calibrating the mean model predictions against the HUD dataset, as discussed in section E.2.2. The value found to best fit the data was 0.0015% of the wall surface area per year. The coverage density was estimated based on information in EPA's Wall Paint Exposure Model (USEPA 2001).

As discussed above, the tracking flux (*TrackingFlux)* is parameterized based on information in Von Lindern et al. (2003) and Thatcher and Layton (1995). Von Lindern et al. (2003) measured the amount of particulate deposited on front mats in 276 houses in two locations near the Bunker Hill Superfund Site. The lead levels reported in the paper are expected to be high-end and are not expected to represent general population exposures. This approach assumed, however, that the rate of accumulation of dust on doormats is not strongly affected by the location and can be used to represent a national population of homes. A distribution was developed by combining the data in the two locations in the 1998 site-wide analysis and estimating a geometric mean and geometric standard deviation for the pooled data. The central tendency estimate is the average of the estimated distribution. In addition, Thatcher and Layton (1995) measured the difference between particulate accumulation in tracked and untracked areas in the home as well as the amount on the front mat. This approach assumed that 75% of the home will contain tracked dirt, and the other 25% consists of corners or other less accessible areas in which people do not walk as frequently. Based on this assumption and the information about the amount of mass on the front mat, the tracked areas of the home, and the untracked areas of the home in Thatcher and Layton (1995), 10% of mass on shoes remains on the front mat (*MatFrac*) and 90% is carried into the homes. Such an assumption may be particularly reasonable in homes with children, as children are less likely than adults to wipe their feet carefully as they enter the home. Previous assessments have used different assumptions. The DIRT model (Johnson, 2008) assumed that the mass capture on the mat in the von Lindern study represented the total mass entering the home. For that model, a range of 50-300 mg/day was reported, and a mass flux of 200 mg/day was assumed for urban environments. This is lower than the average of approximately 1,100 mg/day in the current approach. As will be discussed below, however, this higher mass flux is in more agreement with the relative contribution to dust from outdoor soil reported in Adgate et al. (1998) and the average organic fraction in dust.

Cleaning efficiency (*CE*) has been found to vary according to the type of flooring (carpeting *versus* hard floor) and the total amount of lead on the floor (lower efficiencies for very low lead loadings, due to electrostatic forces attracting the particles to the floor or burial of lead deep into carpet, and higher efficiencies for higher lead loadings). The Environmental Field Sampling Study (EFSS), Volume I: Table 8D-3 (USEPA 1997b) provides pre- and post-cleaning lead loading estimates from a house with hard floors that was subject to a renovation activity and post-activity cleaning. Thus, these estimates likely are higher than routine cleaning efficiencies in a house where no renovation (and no associated elevated lead loading) has occurred. The selected value for *CE* (12.5% removal with each cleaning) represents an approximate midpoint in the lowest lead loading range in the study. These values are similar to values found by Ewers et al. (1994) and Clemson Environmental Technologies Laboratory (2001) for cleaning efficiencies on a carpeted floor after a renovation activity and after three previous cleaning iterations (so that much of the renovation-related lead loading had already been removed and the cleaning was similar to a routine cleaning). The range of efficiency in the literature varies widely. Bero et al. (1997) reported efficiencies of 50% for carpeted areas and 95% for hard floors, representing high-end estimates of efficiency. Roberts et al. (1994), as cited in Qian et al. (2008), reported efficiencies of only 5-10% in older carpets after lead dust exposure. In addition, Ewers et al. (1994) reported that cleaning must be thorough and be carried out for 6 m^2/min to ensure removal of more than 70% of dust from carpets. Qian et al. (2008) assumed efficiencies of 5% based on a lower vacuuming rate of 1 m^2/min, making the assumption that the 6 m^2/min vacuuming rate is rarely achieved in practice.

Cleaning frequency (*CF*) represents a particularly sensitive variable, as will be discussed in section E.2.3. Self-reported cleaning frequency information was listed in the Exposure Factors Handbook (USEPA 1997a) for 4,663 U.S. households. The respondents were asked to answer whether they swept or vacuumed nearly every day, three to five times a week, once or twice a week, once or twice a month, less often, or never. Table E-4 lists the data reported in the survey, and the respondents who reported they never cleaned or did not know were not used in the analysis. An upper bound was assigned to each bin and a geometric mean and geometric standard deviation for the overall data were estimated by calculating the distribution that minimized the squared errors between the actual and predicted cumulative probability distributions. The central tendency estimate is the average frequency in the calculated distribution. This value may indicate more cleanings than are realistic, since the data were self-reported; however, this dataset represents the most reliable one that could be located in the literature.

Overall, the selected cleaning efficiency may represent a value toward the lower bound of available values while the average cleaning frequency may be on the higher end (that is, fewer days between cleanings). This observation may reflect the fact that cleanings that occur more often may not be as thorough and may result in lower efficiencies. One way to cast the overall cleaning removal within the context of other models is to examine the cleaning transfer coefficient, which is defined as the cleaning efficiency divided by the days between cleanings. Table E-5 presents information comparing the cleaning removal rate from the current approach model to other models in the literature. Overall, the cleaning removal rate is on the low end of the literature values but is within the range of available values. The table also highlights the wide uncertainty and/or variability associated with this variable. The approach model attempts to address this variability by sampling the cleaning frequency distribution.

Emissions rates for the generation of particulate due to cooking were taken from the "Indoor Air Quality: Residential Cooking Exposures" final report (State of California's Air Resources Board (CARB 2001)). Experiments in the CARB study included both cooking episodes and oven cleaning; these were separated and oven cleaning was not included in the analysis. The cooking episodes tested tended to include fairly labor-intensive cooking activities such as frying and broiling meat, and the tests were performed on both electric and gas stoves and ranges. A lognormal distribution was estimated by weighting each experimental cooking test equally to calculate the geometric mean and geometric standard deviation of emissions rates.

Emission rates due to the formation of human dander were taken from Gilbert (2003), who reported that the average human generates 1.5 grams of dander per day. The 2001 RECS (USDOE 2001) was used to determine that the average U.S. household has 2.2 people in it. This number was rounded to three and multiplied by the amount of dander generated by each person per day. In addition, information from the CHAD database indicated that people tend to spend 2/3 of their time in the home and 1/3 outside the home on average. Thus, it was assumed that only 2/3 of the dander was emitted in the home. The final estimate, then, incorporates these three assumptions.

The assumption was made that the household members do not smoke in their home. A future refinement to the model could include distributions of smoking generation rates based on the frequency of smoking and assumptions about the number of smokers who smoke in their home as opposed to outdoors.

Finally, the outdoor air particulate rate was determined by examining PM_{10} data from particulate monitors in the AQS monitoring network (USEPA 2010). Data from 1997 were used to match the calibration data sets (see section E.2.2). In general, the particulate mass does not vary as strongly from location to location as the lead mass in the particulate. Thus, the model uses only a central tendency estimate for the particulate concentration based on the average annually-averaged concentration across the AQS monitors.

Table E-3. Inputs for the Mechanistic Model

Variable	Variable Name	Units	Central Tendency Value	Geometric Mean	Geometric Standard Deviation	Source
V	House Volume	m^3	507	390.5	2.06	US DOE (2001)
FloorLoading	Floor area per unit volume	m^2/m^3	0.36	N/A	N/A	USEPA (1997a)
WallLoading	Wall area per unit volume	m^2/m^3	0.98	N/A	N/A	USEPA (1997a)
AER	Air Exchange Rate	h^{-1}	0.63	N/A	N/A	USEPA (1997a)
P	Penetration Efficiency	unitless	1	N/A	N/A	Thatcher and Layton (1995)
D	Deposition Rate	h^{-1}	0.65	N/A	N/A	Value for PM10, USEPA (1997a), adapted from Wallace (1996)
R	Resuspension Rate	h^{-1}	1.4E-04	N/A	N/A	Qian et al. (2008)
ChipFraction	Fraction of wall area that flakes per year	$year^{-1}$	1.50E-05	N/A	N/A	Calibrated
CoverageDensity	Paint Coverage Density	g/m^2	1.25E+02	N/A	N/A	Estimated from paint density and EPA Wall Paint Exposure Model coverage default (US EPA, 2001)
TrackingRate	Tracking Rate	g/day	1.21E-02	7.89E-02	2.52	Von Lindern et al. (2003)
MatFrac	Fraction of tracked material remaining on the mat	unitless	0.1	N/A	N/A	Estimated based on data in Thatcher and Layton (1995)
CE	Cleaning Efficiency	unitless	0.125	N/A	N/A	Estimated based on data in Battelle Memorial Institute (1997)
CF	Cleaning Frequency	days between cleanings	3.5	3.27	1.78	USEPA (1997a)
CookingRate	Cooking Rate	g/day	0.35	N/A	N/A	CARB (2001)
DanderRate	Dander Rate	g/day	3.015	N/A	N/A	Estimated from information in Gilbert (2003)
SmokingRate	Smoking Rate	g/day	0	N/A	N/A	Assumption
PartAir	Outdoor Air Particulate Concentration	g/m^3	2.36E-05	N/A	N/A	Based on analysis of AQS data (USEPA, 2010)

Table E-4. Cleaning Frequency Data from the Exposure Factors Handbook

Frequency	Number Of Respondents	Percentage
Nearly Every Day	921	20%
Three to Five Times a Week	1108	24%
Once or Twice a Week	2178	47%
Once or Twice a Month	373	8%
Less Often	48	1%
Never	10	0%
Did Not Know	25	1%

Table E-5. Comparison of Cleaning Transfer Coefficients in Mass Balance Models

	Cleaning Efficiency (unitless)	Days Between Cleanings (d)	Transfer Coeff (d^{-1})
Layton and Beamer (2009)	N/A	N/A	5.30E-03
Qian et al. (2008)	0.05	7	7.14E-03
Approach Model	**0.125**	**2.5**	**5.00E-02**
Johnson (2008)	0.725	14	5.18E-02

E.2.2 Sensitivity Analysis

In order to determine the parameter values to which the model predictions are most sensitive, a preliminary sensitivity analysis was carried out. First, the media concentrations and other sampled variables were set to their mean values for the HUD dataset. Then, each variable was separately increased by 5% to determine the percent change in the floor loading, the floor concentration, and the slope. The percent changes were then divided by the percent change in the input (5%) to derive the elasticities. Comparison of the absolute value of elasticities across the different variables provides information about the variables to which the model is most sensitive.

Table E-6 shows the elasticities for each variable, where the table is sorted in decreasing order by the absolute value of the slope elasticities. None of the elasticities is greater than 1, indicating that changing a variable by 5% changes the slope by less than +/- 5%. The model is most sensitive to the cleaning frequency, the floor loading, the house volume, and the cleaning efficiency. To date, the model samples the cleaning frequency, but not the other three variables. The literature does not currently have reliable information to allow building a distribution of cleaning efficiencies. The sensitivity analysis, however, suggests that the model should sample both house volume and floor area loading in a future implementation in order to capture the variability in these variables. The model also displays moderate sensitivity to the dander generation rate, the fraction of material staying on the floor mat, the soil tracking rate, the deposition rate, and the air exchange rate.

Table E-6. Elasticities for Each Variable in the Model

Variable	Variable Description	Floor Loading	Floor Concen.	Slope
CF	Cleaning Frequency	0.97	0.00	**0.97**
FloorLoading	Floor Area Loading	-0.95	0.00	**-0.95**
V	House Volume	-0.30	0.66	**-0.93**
CE	Cleaning Efficiency	-0.92	0.00	**-0.92**
DanderRate	Dander Rate	0.00	-0.52	**0.53**
MatFrac	Fraction of tracked material remaining on the mat	-0.33	0.07	**-0.40**
TrackingRate	Tracking Rate	0.31	-0.06	**0.38**
D	Deposition Rate	0.10	-0.21	**0.31**
AER	Air Exchange Rate	0.07	0.36	**-0.29**
CookingRate	Cooking Rate	0.00	-0.06	**0.06**
R	Resuspension Rate	-0.03	0.00	**-0.03**
PartAir	Outdoor Air Particulate Concentration	0.00	-0.03	**0.03**
WallLoading	Wall area per unit volume	0.52	0.52	**0.00**
ChipFraction	Fraction of wall area that flakes per year	0.52	0.52	**0.00**
CoverageDensity	Paint Coverage Density	0.00	0.00	**0.00**
PbAirConcen	Ambient Air Lead Concentration	0.17	0.17	**0.00**
PbSoilConcen	Soil Lead Concentration	0.31	0.31	**0.00**
PbPaintConcen	Paint Lead Concentration	0.52	0.52	**0.00**

E.2.3 Calibration and Comparisons to Datasets

Two datasets were identified for use in calibrating and evaluating the model for residences. The first is the HUD survey of lead in homes (USEPA 1998). This survey provides paint concentrations (as XRF readings), yard soil concentrations, indoor dust lead loading wipe samples and indoor dust lead concentrations for 284 homes. These homes, when combined with their respective weights, are intended to be nationally representative of lead levels in the US housing stock in 1997.

In order to compare the model predictions to the survey results, the AQS data were used to estimate the distribution of lead in total suspended particles (TSP) in 1997 (USEPA 2010). Available lead monitoring results were averaged to give yearly averages and a lognormal distribution was developed based on the range of values across the different monitors. In addition, distributions of paint concentration and soil concentration were developed from the HUD data from homes built before 1980. The model was then run under the assumption of three different cleaning frequencies (once a week, twice a week, and twice a month) based on the range of cleaning frequencies in the Exposure Factors Handbook (USEPA 1997a). To generate each of the 100 model points, the soil, paint, and air concentration distributions were sampled to generate a combination of estimates, and the model equations were applied to calculate the floor loading and the slope. Figure E-3 shows the lead loadings and corresponding concentrations for the HUD data and the model predictions. The regression equation discussed in Section E.1 is also shown for reference.

For a given cleaning frequency, the mechanistic model predictions fall in a straight line defined by the slope equation above. Because this equation does not depend on the soil, paint, and air concentrations and because nothing else was sampled in the development of the figure, the slope is constant for a given cleaning frequency. The slope tends to decrease in homes in which cleaning occurs less frequently. The national average cleaning frequency in the Exposure Factors Handbook is approximately two cleanings per week; thus, the paint flaking fraction variable (*ChipFraction*) was adjusted until the slope was in good agreement with the regression line for loadings up to the 75th percentile loading (a value of approximately 17.3 μg/ft^2). Note that the other two cleaning frequencies represent high and low bounds estimates for the population (cleaning every day represents the 2nd percentile while cleaning once every two weeks represents the 99.5th percentile from the estimated cleaning frequency distribution) and they bound the majority of the loading and concentration data points.

The model predicts a straight line for a given cleaning frequency, while the regression suggests a nonlinear relationship. One possible interpretation of this discrepancy is that most of the higher loadings likely occur in homes that are vacuumed less often. Thus, as one moves along the loading axis, a change in cleaning frequency leads to a change in the slope of the loading-concentration relationship.

Once this initial calibration step was complete, the model was run again by sampling additional variables where distributions existed; thus, in addition to the soil, paint, and air concentrations, the soil tracking rate and cleaning frequency were also sampled. The resulting model points are shown along with the raw HUD data in Figure E-4. These model values provide a suitable spread across the actual data. In order to quantify the model performance, Table E-7 provides a comparison of the average and median loadings and concentrations. The model tends to underpredict the mean loadings and concentrations; the means are more affected by the outliers, suggesting that the central tendency values used for most variables may not be sufficient to capture the very high loadings and concentrations. The model is able to capture the median loadings and concentrations, however, which still reflect the distribution, but are not as affected by outliers.

Table E-8 compares model metrics to values found in the literature for data or from other models. Adgate et al. (1998) provided estimates of the fraction of the loading arising from the air, soil, and paint sources in homes in Jersey City, NJ. The model tends to predict more lead arising from paint sources and less from soil sources than in the Adgate study. The Jersey City homes in the Adgate study, however, tended to be in urbanized areas with higher average soil concentrations than in the nationally-representative HUD dataset. Also shown is the average indoor/outdoor air ratio in 35 California homes for PM_{10} from Colome et al. (1992). The model predicts a ratio very close to this value, which provides further support to the fact that the model parameters are not merely tuned, but may be reflecting the actual physical processes at work in the homes. The model predicts that about 66% of indoor dust mass arises from indoor sources of organic material (e.g., cooking, human dander). After analyzing the dust in four homes in England, Allott et al. (1994) concluded that 42% +/- 17% arose from organic sources. This suggests the model prediction is within the range found in the four homes in the study and lends support to the relative contribution from soil, paint, air, and indoor sources to indoor dust.

Figure E-3. Modeled Loading-to-Concentration Relationships for Three Different Cleaning Frequencies

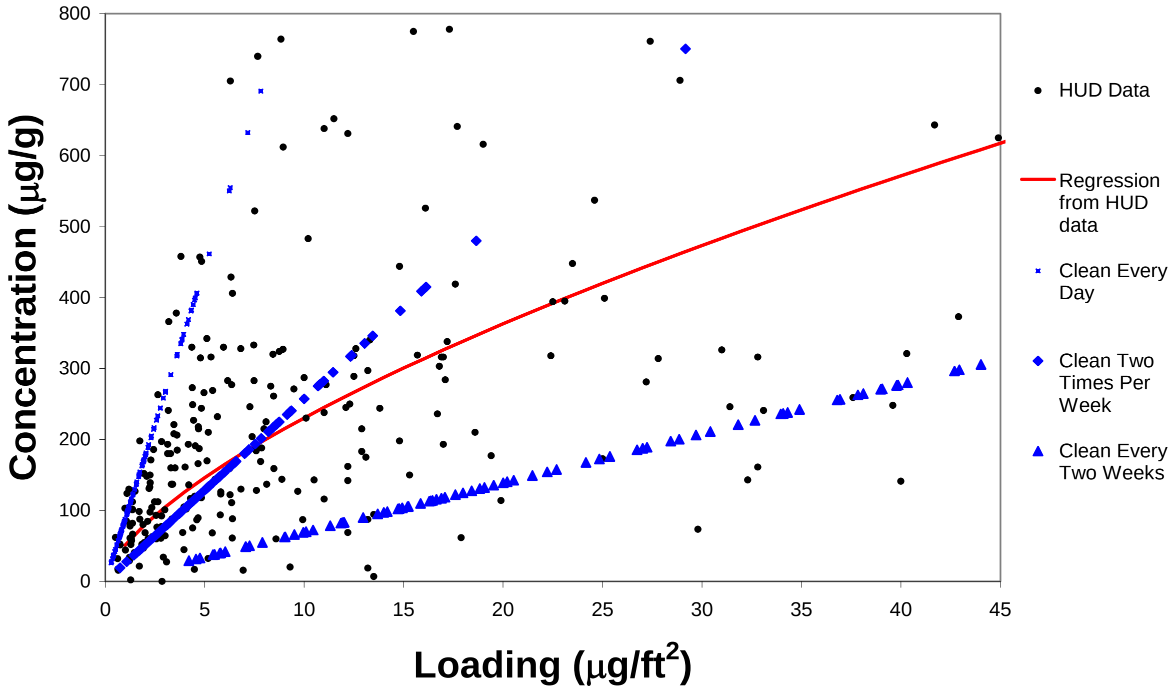


Figure E-4. Modeled Loading and Concentration Values Using HUD Air, Paint, and Soil Distributions and Distributions for Soil Tracking and Cleaning Frequency

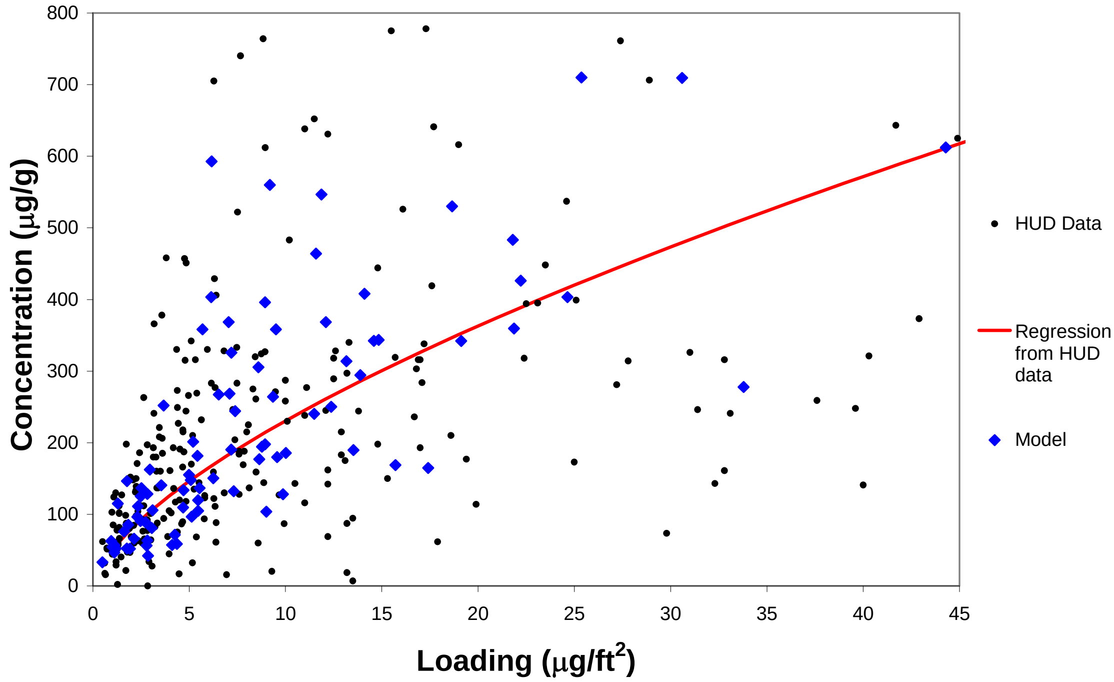


Table E-7. Comparison Between Modeled and Actual Loadings and Concentrations

	Mean Load	Mean Concen	Median Load	Median Concen
HUD Data	21	559	7.4	201
Model	13	336	7.3	188

Table E-8. Comparison Between Modeled and Actual Loadings and Concentrations

	% Air	% Soil	% Paint	Indoor / Outdoor Air Ratio	% Indoor Dust from Organic Sources
Literature	17%[a]	49%[a]	34%[a]	0.7[b]	42% +/- 17%[c]
Model	38%	13%	49%	0.63	66%

[a] From Adgate et al. (1998)
[b] From Colome et al. (1992)
[c] From Allott et al. (1994)

Once the calibration was complete, the model was applied to a second dataset as a further model evaluation. Lanphear et al. (1998) collected data for 205 children in Rochester, NY. As part of the blood lead evaluation, they collected lead dust loading samples, lead concentration samples, indoor XRF lead paint concentrations, and play yard and house perimeter lead soil samples. Samples were collected in multiple areas and a composite was estimated as the average or median sample value. Distributions were generated from the lead paint concentrations and play yard soil lead concentrations for use in the model. It was assumed that the play yard soil would be more readily tracked into the home than would be the house perimeter soil. The AQS monitoring network was used to calculate lead concentrations in the ambient air. A distribution was generated by finding the monthly average concentrations for data from 1993-1996, along with the geometric mean and geometric standard deviation. The model was then applied to the dataset with no other modifications. The lead air concentration, lead soil concentration, lead paint concentration, soil tracking rate, and cleaning frequency were all sampled and modeled for 100 realizations and compared to the median of the floor lead loading and concentration estimates. Figure E-5 provides a comparison between the modeled and actual data. As in the HUD dataset, the spread and pattern of modeled data are consistent with the actual data. Note that the spread of the data is larger in the Rochester data than in the HUD data, likely due to much larger average soil concentrations. Also shown for reference is the regression line calculated from the HUD data and the regression line calculated directly from the Rochester data. The regression lines predict similar relationships at higher loadings, but differ by 25-50% for loadings between 10 and 40 $\mu g/ft^2$.

Table E-9 compares the modeled and actual means and medians along with the source contribution percentages and outdoor/indoor air ratios. Overall, the model does well at predicting the medians, although it tends to underpredict the means as in the HUD dataset. Table E-10 compares other model metrics to the values in the literature. The source percentages are more similar to the Adgate data, perhaps because the Rochester homes are more comparable with the Adgate Jersey City homes; however, the model still tends to contribute more from paint and less from soil than the Adgate data suggest. The indoor/outdoor ratio is still within range of the mean value from Colome et al. The percentage of dust mass arising from indoor sources is the same as in the HUD model, since this value does not rely on any of the lead media concentration values.

Figure E-5. Modeled Loading and Concentration Values Using Rochester Air, Paint, and Soil Distributions and Distributions for Soil Tracking and Cleaning Frequency

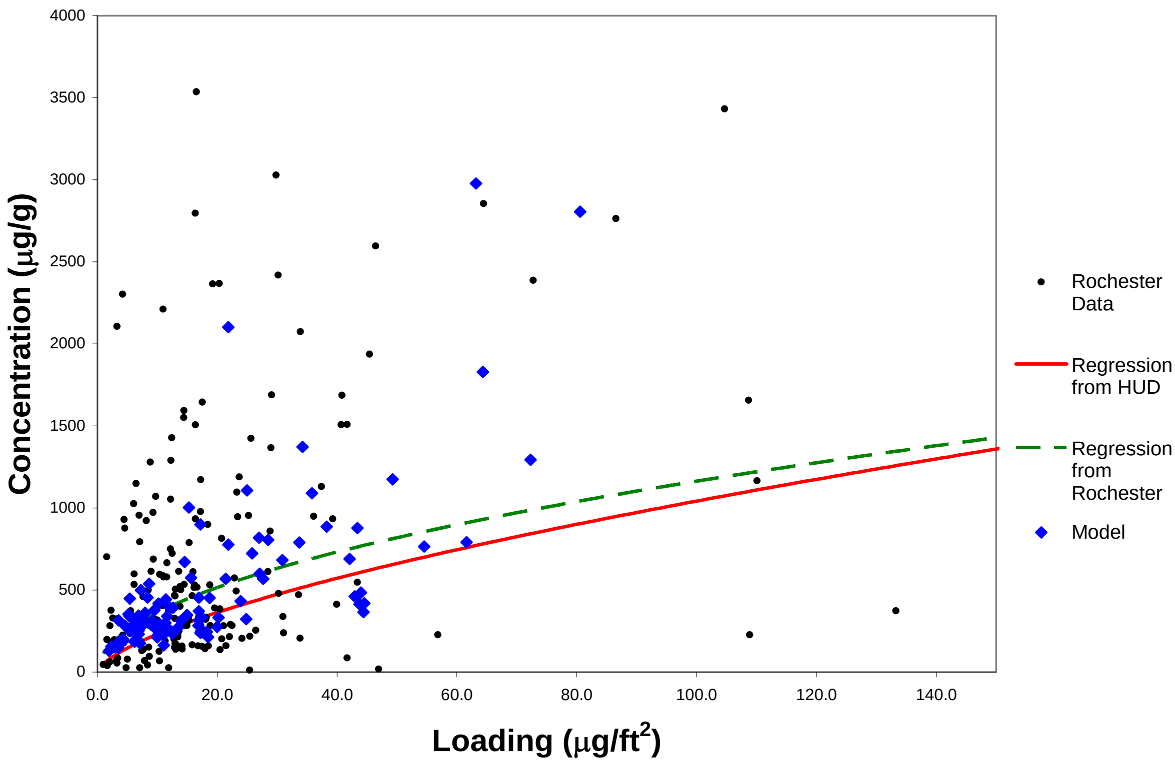


Table E-9. Comparison Between Modeled and Actual Loadings and Concentrations

	Mean Load	Mean Concen	Median Load	Median Concen
Rochester Data	21	776	14	370
Model	20	590	13	342

Table E-10. Comparison Between Modeled and Actual Loadings and Concentrations

	% Air	% Soil	% Paint	Indoor / Outdoor Air Ratio	% Indoor Dust from Organic Sources
Literature	17%[a]	49%[a]	34%[a]	0.7[b]	42% +/- 17%[c]
Model	16%	27%	57%	0.63	66%

[a] From Adgate et al. (1998)
[b] From Colome et al. (1992)
[c] From Allott et al. (1994)

E.3 Strengths and Limitations of the Loading-Concentration Conversion Models

As identified in Section 3.2.3, each of these two alternative methods to convert the loadings to concentrations has strengths and limitations. The regression equation is based on a nationally-representative dataset with sufficient samples across different housing vintages, outdoor soil concentrations, and indoor paint concentrations. The regression equation is most reliably applied in the range of loadings and concentrations seen in the original dataset, and the hazard standard is expected to fall within that range. The regression equation does not allow any incorporation of variability due to the difference in physical attributes and cleaning patterns among homes. The underlying data show a wide spread across the loading-concentration parameter space, indicating wide house-to-house variability.

The mechanistic model, on the other hand, will allow for extension of the model to public and commercial buildings, provided the physical processes are described adequately and the proper input values can be developed, thereby allowing the residential and public and commercial buildings standards to have a common footing. Because the public/commercial buildings tend to be larger, more people come in and out of the buildings daily (thus introducing more dander to the indoor environment and diluting the indoor dust), and the cleaning patterns are different, these buildings can be expected to have a very different loading-to-concentration relationship from houses. However, the model assumes that the indoor environment is well-mixed and contains no concentration gradients; thus, it also can be applied to any portion of the public/commercial building where this assumption is valid. The mechanistic model also allows for the loading to concentration conversion to incorporate house-to-house variability. The model is subject to uncertainty, however, because of the relatively simple form of the physical equations and the absence of information about some of the variable inputs. The model has been calibrated against the HUD dataset and then compared to one additional dataset, and the model is expected to return reasonable estimates for the national population in the range of the hazard standard. There currently is no relationship between window sill loading and concentration, however, and unless such a slope is developed, the same slope as used for the floor dust would have to be used in developing the window sill hazard standard.

In addition, the mechanistic model uses the steady state solution to the model equations. One assumption is made in the development of these equations, however, which affects the solution. When the steady state equations are solved, an assumption is made that routine cleaning happens continuously at a rate equal to the cleaning frequency. In reality, however, the cleaning occurs in discrete episodes once per cleaning cycle. This assumption introduces some error into the slope, loading, and concentration estimates, and this error increases with increasing numbers of days between cleaning. Table E-11 shows a representative sample of the slope and loadings under the assumption of episodic and continuous cleaning for ten of the 200 model realizations. For cleaning every two weeks, the error in the slope is up to 14.5%; however, at the average cleaning frequency (about two cleanings per week), the error is only an average of 7.0% (maximum of 9.5%). The errors in the loadings are comparable, and the errors in the concentrations are only an average of 0.5% (maximum of 0.7%). Thus, this assumption, which is necessary from a practical standpoint in the development of the hazard standard in order to avoid numerous iterations of the model, introduces error that is not too great in the region of expected cleaning frequencies.

While attempts have been made to take into account variability across homes by sampling some of the input parameters, no attempt has been made to account for variability within a home. Unlike the DIRT model (Johnson, 2008), which predicts gradients across floors and carpets, the model treats the home as a uniform environment. Differences across carpets and floors and between high traffic areas and less accessible areas are not accounted for in the model, and the assumption is made that the model captures the mean characteristics of the heterogeneous home.

Table A-11. Representative Realizations Demonstrating the Error When Considering Continuous Cleaning Compared to Episodic Cleaning

Reali-zation	Outdoor Air Concen. (μg/m3)	Soil Concen. (μg/g)	Paint Concen. (μg/g)	Tracking (g/day)	Clean. Freq. (days between clean.)	Floor Loading, Episodic Clean.	Floor Concen, Episodic Clean.	Slope, Episodic Clean.	Floor Loading, Contin. Clean.	Floor Concen. Contin. Clean.	Slope, Contin. Clean.	% Error in Load.	% Error in Concen.	% Error Slope
1	9.39E-02	1.39E+02	1.11E+00	9.50E-02	2.38E+00	6.04E+00	2.69E+02	2.25E-02	6.45E+00	2.67E+02	2.42E-02	6.8%	-0.5%	7.3%
5	4.12E-02	6.80E+01	2.10E+00	1.78E-02	3.74E+00	7.93E+00	3.08E+02	2.58E-02	8.43E+00	3.06E+02	2.76E-02	6.3%	-0.7%	7.0%
9	4.32E-03	9.61E+00	2.53E+01	1.20E-01	9.47E-01	1.80E+01	1.81E+03	9.96E-03	1.92E+01	1.80E+03	1.07E-02	6.5%	-0.5%	7.0%
13	2.50E-02	4.41E+01	8.20E-01	1.33E-01	2.52E+00	2.87E+00	1.06E+02	2.70E-02	3.06E+00	1.06E+02	2.89E-02	6.5%	-0.4%	7.0%
17	4.82E-02	7.79E+01	1.69E+00	2.79E-01	5.72E+00	1.44E+01	1.69E+02	8.49E-02	1.53E+01	1.69E+02	9.05E-02	6.3%	-0.3%	6.6%
21	2.04E-02	3.69E+01	9.95E-01	3.10E-02	3.15E+00	3.28E+00	1.42E+02	2.32E-02	3.49E+00	1.41E+02	2.48E-02	6.6%	-0.6%	7.2%
25	3.06E-03	7.11E+00	2.96E-01	5.28E-02	1.70E+00	4.66E-01	3.34E+01	1.39E-02	4.97E-01	3.32E+01	1.50E-02	6.6%	-0.6%	7.3%
29	2.41E-02	4.27E+01	9.28E-01	7.75E-02	2.05E+00	2.30E+00	1.26E+02	1.83E-02	2.46E+00	1.25E+02	1.96E-02	6.7%	-0.5%	7.3%
33	1.49E-01	2.07E+02	6.02E-01	4.05E-02	3.18E+00	8.78E+00	3.60E+02	2.44E-02	9.34E+00	3.58E+02	2.61E-02	6.4%	-0.6%	7.0%
37	4.34E-01	5.24E+02	1.38E+00	5.50E-02	1.80E+00	1.44E+01	9.76E+02	1.48E-02	1.54E+01	9.70E+02	1.59E-02	6.9%	-0.6%	7.5%
41	3.62E-02	6.08E+01	8.21E-01	1.27E-01	1.93E+00	2.63E+00	1.29E+02	2.04E-02	2.80E+00	1.28E+02	2.18E-02	6.4%	-0.4%	6.9%
45	9.97E-03	1.98E+01	1.26E+00	5.72E-02	6.35E+00	6.67E+00	1.33E+02	5.02E-02	7.08E+00	1.32E+02	5.36E-02	6.2%	-0.6%	6.8%
51	2.38E-02	4.22E+01	3.69E+00	1.46E-01	1.50E+00	4.80E+00	2.91E+02	1.65E-02	5.24E+00	2.90E+02	1.81E-02	9.1%	-0.4%	9.5%
55	7.05E-02	1.08E+02	6.93E-01	2.47E-02	1.95E+00	3.10E+00	2.19E+02	1.42E-02	3.30E+00	2.17E+02	1.52E-02	6.7%	-0.7%	7.4%
59	7.43E-02	1.13E+02	8.81E-01	1.26E-01	1.36E+00	2.97E+00	2.05E+02	1.45E-02	3.16E+00	2.04E+02	1.55E-02	6.5%	-0.5%	6.9%
63	2.70E-01	3.48E+02	8.28E-01	2.70E-02	8.63E+00	3.76E+01	6.42E+02	5.86E-02	3.99E+01	6.38E+02	6.25E-02	6.1%	-0.6%	6.8%
67	1.68E-02	3.12E+01	2.12E+00	3.84E-02	3.03E+00	5.52E+00	2.39E+02	2.31E-02	5.86E+00	2.37E+02	2.47E-02	6.2%	-0.6%	6.8%
71	1.13E-01	1.64E+02	2.74E+00	4.59E-02	4.44E+00	1.66E+01	4.85E+02	3.42E-02	1.77E+01	4.82E+02	3.67E-02	6.5%	-0.6%	7.1%
75	1.50E+00	1.54E+03	1.43E+00	9.95E-02	6.89E+00	1.77E+02	2.80E+03	6.31E-02	1.88E+02	2.79E+03	6.72E-02	6.1%	-0.5%	6.6%
79	7.27E-02	1.11E+02	3.63E+00	4.01E-02	8.42E+00	3.00E+01	4.95E+02	6.06E-02	3.18E+01	4.92E+02	6.47E-02	6.1%	-0.6%	6.7%
83	2.24E+00	2.18E+03	9.50E-01	6.81E-03	2.94E+00	9.48E+01	4.89E+03	1.94E-02	1.01E+02	4.86E+03	2.08E-02	6.4%	-0.7%	7.2%
87	1.38E-03	3.57E+00	2.60E+00	1.63E-01	5.21E+00	9.80E+00	1.66E+02	5.89E-02	1.04E+01	1.66E+02	6.29E-02	6.3%	-0.4%	6.8%
91	7.98E-01	8.90E+02	4.50E+00	7.50E-01	5.79E+00	2.00E+02	1.17E+03	1.71E-01	2.13E+02	1.17E+03	1.81E-01	6.1%	-0.2%	6.3%
95	1.66E-01	2.27E+02	6.24E-01	5.89E-02	2.83E+00	9.01E+00	3.85E+02	2.34E-02	9.61E+00	3.83E+02	2.51E-02	6.7%	-0.6%	7.3%
100	1.26E-01	1.79E+02	1.25E+00	1.01E-01	2.29E+00	7.48E+00	3.36E+02	2.22E-02	7.96E+00	3.34E+02	2.38E-02	6.4%	-0.5%	6.9%

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